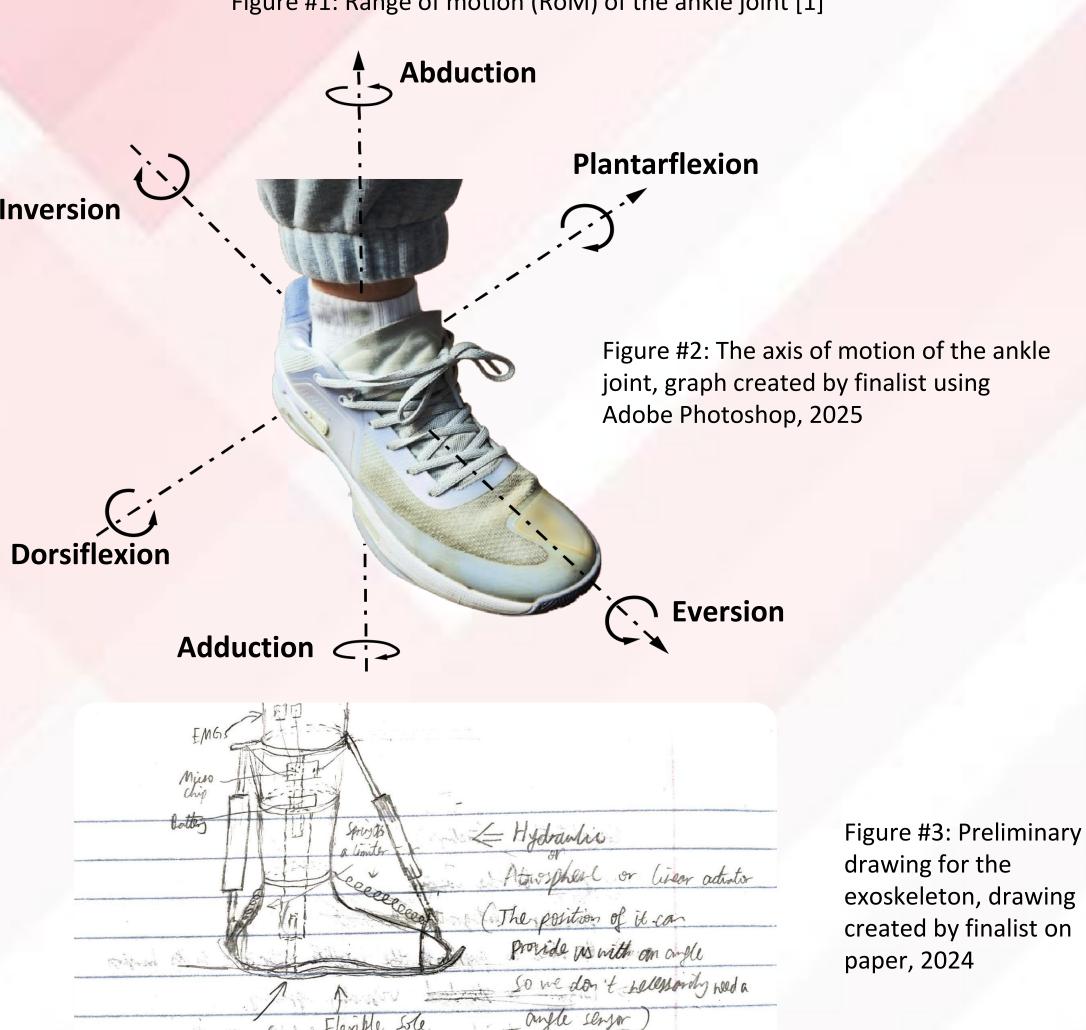
Introduction

Recent ankle rehabilitation research has introduced the use of robotic exoskeletons to enhance muscle strength and correct gait. Fixed-position robots assist in early-stage training but cannot be used while walking. Wearable exoskeletons support walking but struggle with foot rotation along the z-axis. Full lower-limb devices offer broader support but are bulky and not specialized for ankle injuries, making them less convenient. This research aims to address these limitations.

Structural Design

| Motion Direction | ROM (Degree) |
|-------------------------|--------------|
| Dorsiflexion | 20.3–29.8 |
| Plantarflexion | 37.6–45.8 |
| Inversion | 14.5–22.0 |
| Eversion | 10.0–17.0 |
| Abduction | 15.4–25.9 |
| Adduction | 22.0–36.0 |

Figure #1: Range of motion (RoM) of the ankle joint [1]

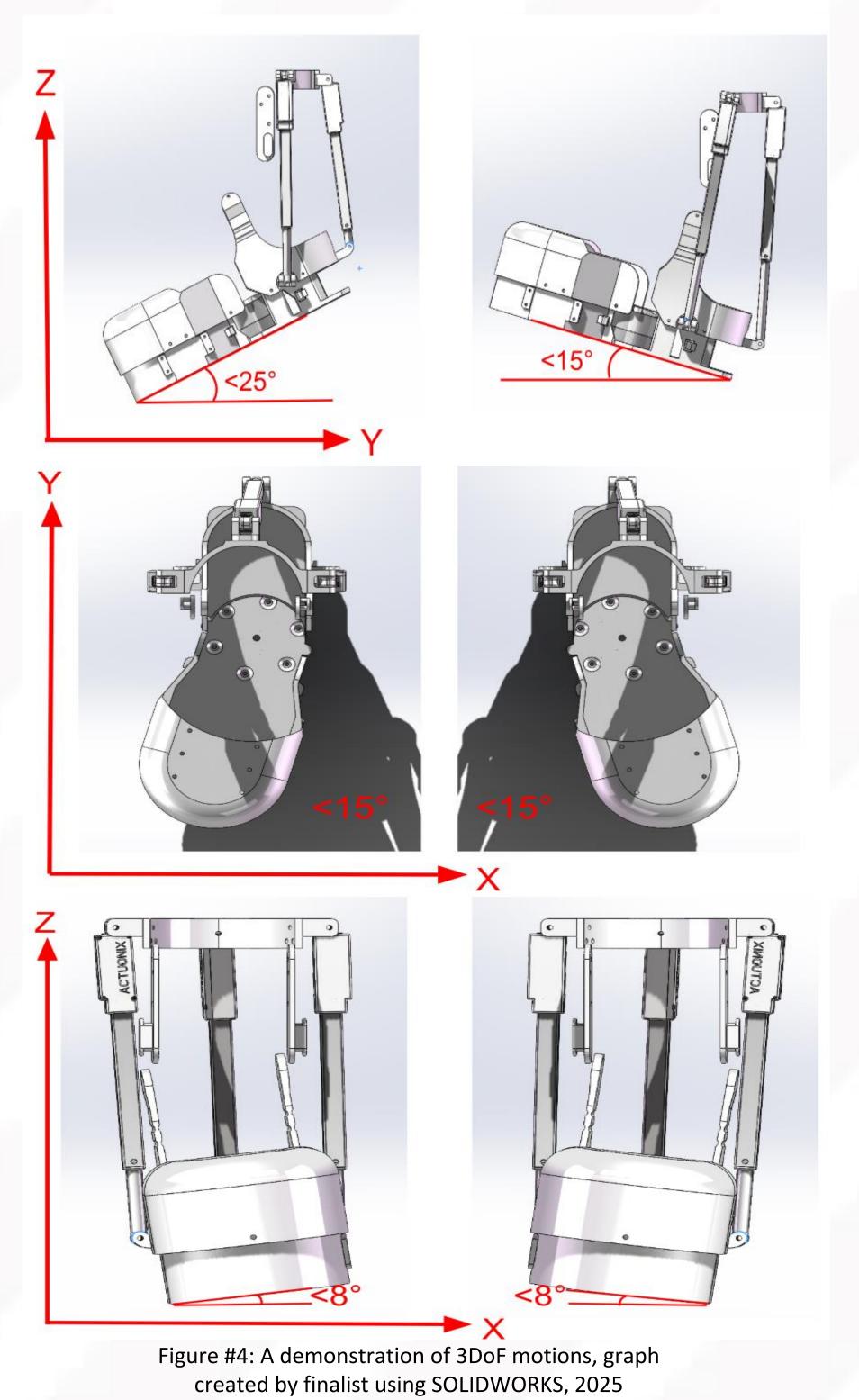


Requirements

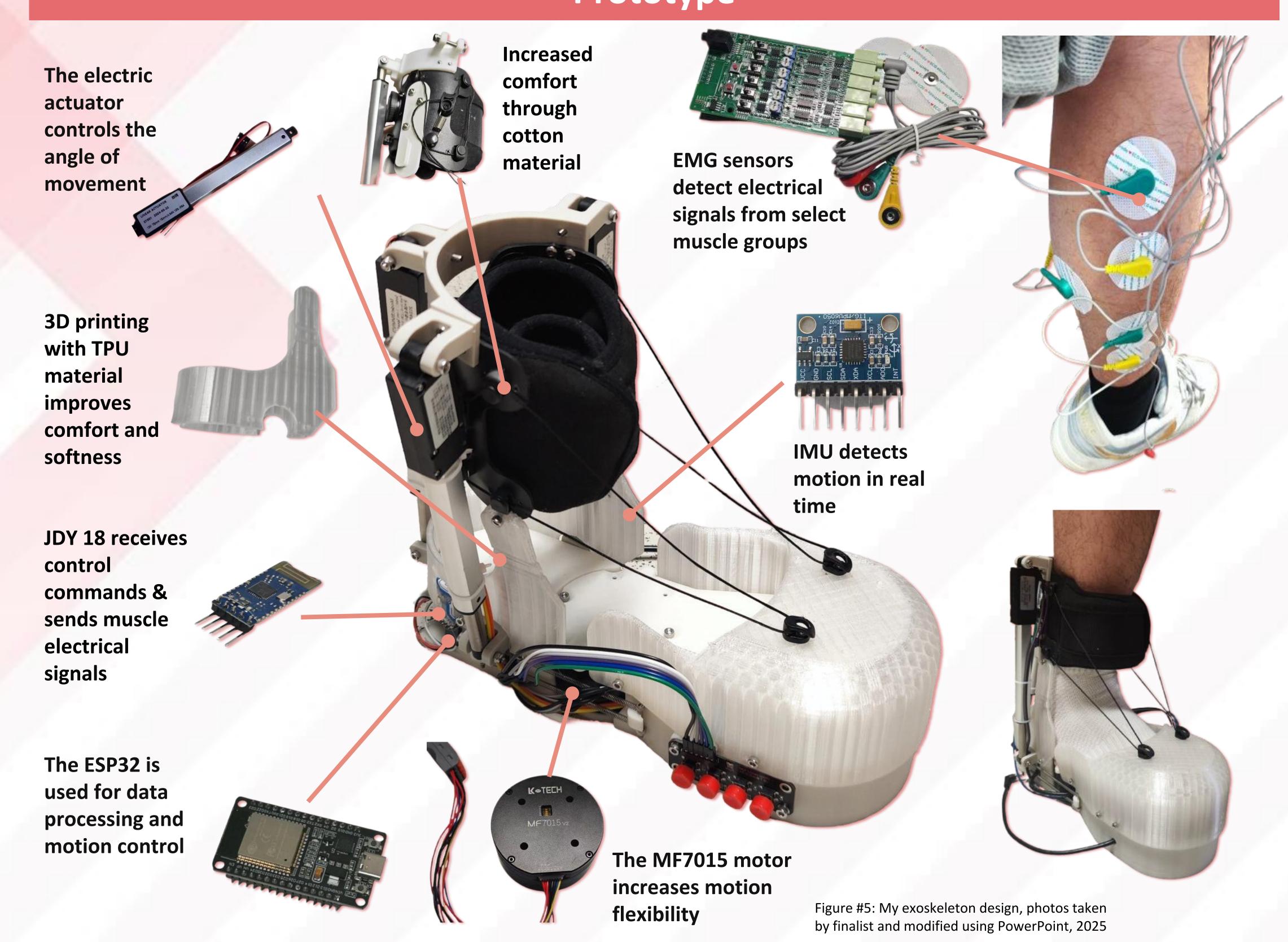
- Support & Stability: The exoskeleton must provide support while allowing movement for rehabilitation
- Natural Motion: Designed to support all six directions of motion (see Fig. 1 & 2)
- Safety Mechanisms: Include mechanical stops or limiters to prevent excessive joint movement
- Sensors: Supports electromyography (EMG) and inertial measurement units (IMU) to monitor muscle activity and gait

Design

- Materials: Made of thermoplastic polyurethane (TPU), carbon fiber reinforced polylactide (PLA-CF), and a commercially available ankle brace for a balance of rigidity and comfort
- Actuation: Uses linear actuators and stepper motors to generate sufficient force (see Fig. 4)
- Component Housing: A chamber under the foot platform accommodates the microcontroller, battery, and motor drivers for efficient space use and easy access
- Degrees of Freedom: Provides 3 Degrees of Freedom (3DoF) to enable natural movement while assisting rehabilitation (see Fig.



Prototype



Algorithm for the Al Model

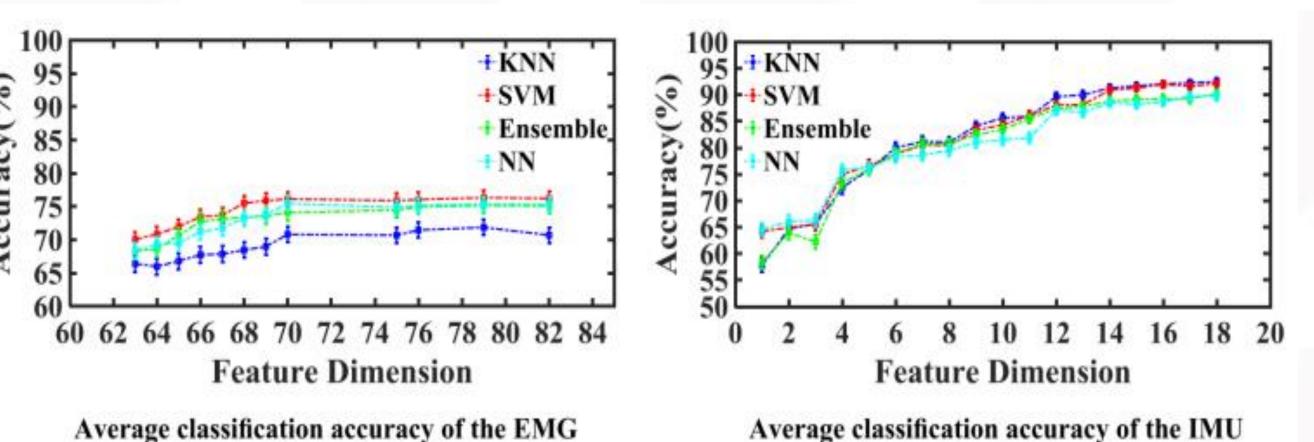


Figure #6: Average classification accuracy as a function of the feature dimension vector [2]

Feature extraction

feature dimension vector

stance and swing phases

for smooth, adaptive assistance

GPR Effectiveness: Accurately estimated actuator torque

Figure #9: Changes in EMG data during walking, graph created by finalist using SerialPlot, 2025

Data collection

- Machine (SVM) for Vector Support Classification: Identifies gait phases using EMG and IMU signals, distinguishing stance and swing
- Gaussian Process Regression (GPR): Predicts optimal actuator torque based on deviations from a healthy gait Dynamic Support: Ensures personalized
- movement correction by responding to muscle activity and motion patterns
- **High Accuracy**: The model reaches an accuracy of 91.66% for classification (see Fig. 6)

Issuance of control

commands

Machine learning

Figure #7: The process of motion state analysis, graph created by finalist using PowerPoint, 2025

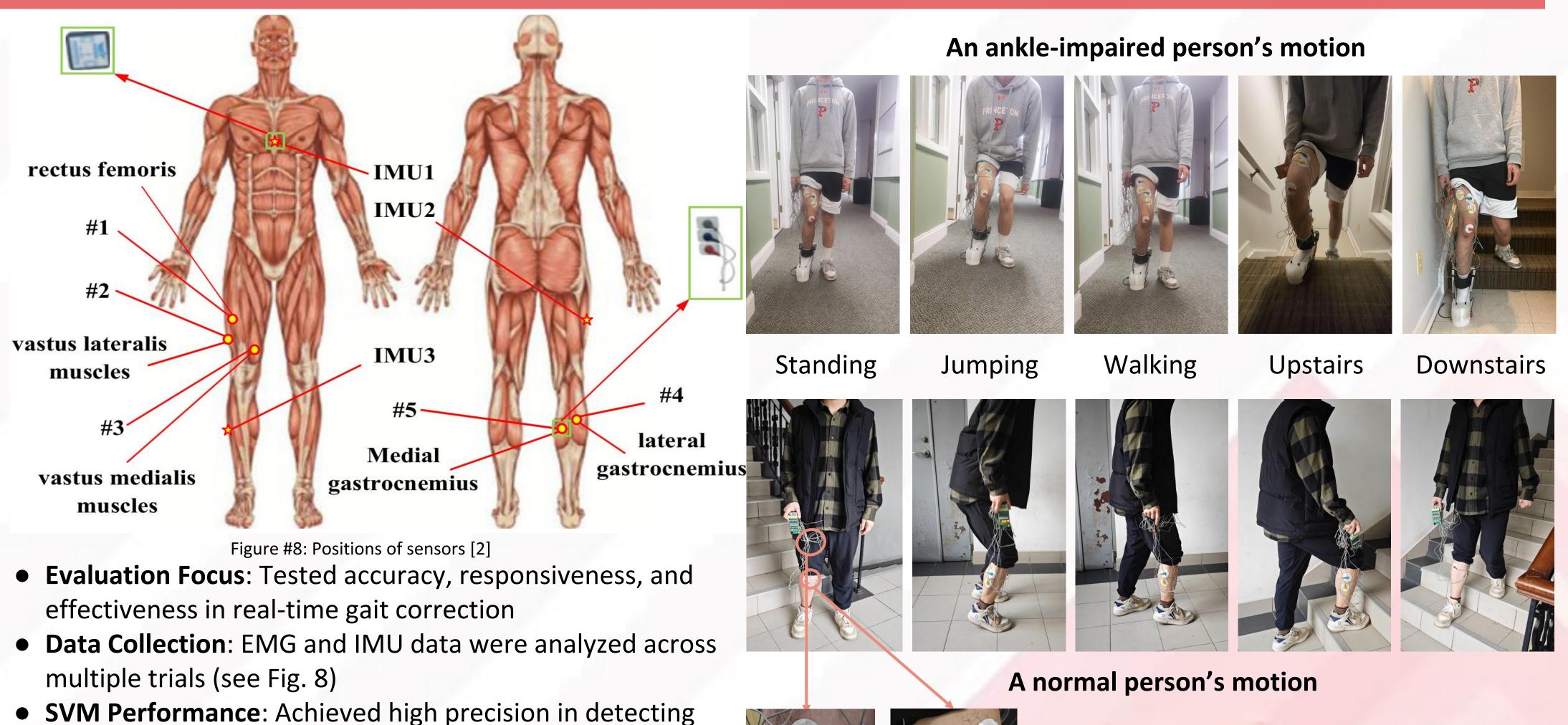
Feature selection and

dimensionality

reduction

Experiments and Analysis

feature dimension vector



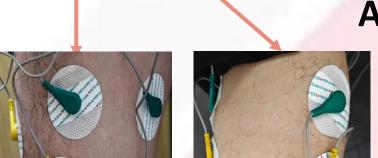


Figure #10: Comparison of a normal person and an ankle-impaired person's motion, photos taken by finalist and modified using PowerPoint, 2025

The results show improved gait symmetry and a 70% reduction in muscle strain, confirming effective real-time support. Comparative trials demonstrated better step consistency and weight distribution with the exoskeleton. This was further supported by differences observed in EMG signals between assisted and unassisted walking (see Fig. 9). Minor issues like response latency and weight balance were noted, suggesting future improvements in the actuator speed and ergonomics. These findings validate the system's potential for personalized ankle rehabilitation.

Embedded System

Real-Time Processing Microcontroller Unit (MCU) processes signals for adaptive control and

rehabilitation assistance

Integration Six-channel EMG detects muscle activation; IMU tracks motion, acceleration, and velocity

Sensor

Control The embedded controller sends commands to motor drivers for precise

movement assistance

Actuator

Power Management

Regulates energy use, optimizes battery life and prevents overheating

Wireless Communication

Enables remote data transmission for adjustments

Efficiency & Adaptability

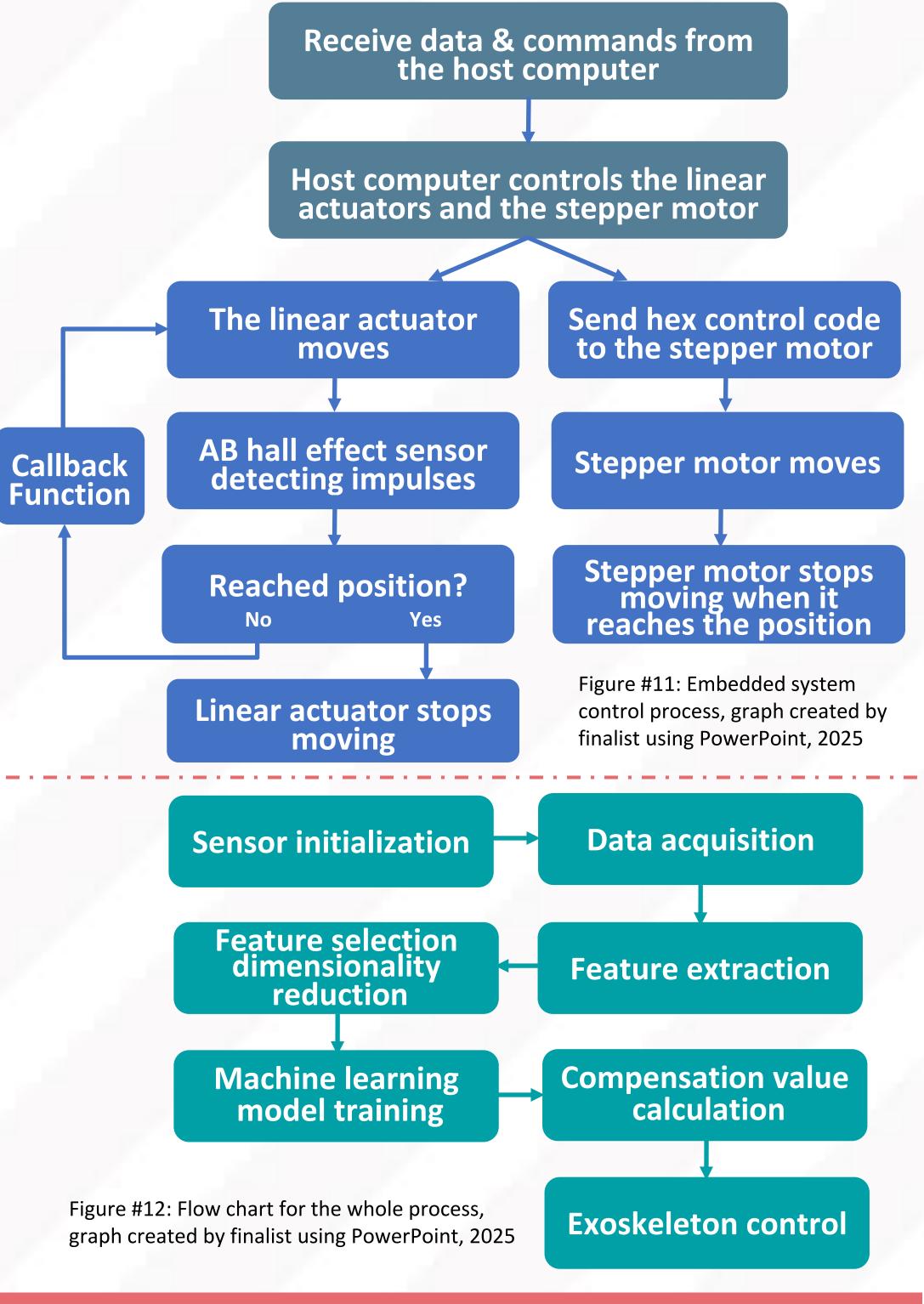
Ensures real-time

user-friendly

responsiveness and

rehabilitation support

Control System



Conclusion

This study successfully developed and validated a real-time adaptive ankle exoskeleton using SVM and GPR to deliver personalized support. The system improved gait symmetry and reduced muscular strain, demonstrating its potential as an intelligent rehabilitation device. With a total cost of approximately \$330, which is significantly lower than that of most existing solutions, the exoskeleton offers a more affordable option for clinical and personal use. In the future, improving response speed, comfort, and power consumption will make the exoskeleton easier to use in clinics and help more people with enabled recovery.

Future Ideas

- Hardware Optimization: Reduce weight with carbon fiber composites and improve battery efficiency
- Software Enhancements: Train SVM and GPR on larger datasets for better gait classification and control
- Latency Reduction: Optimize real-time processing and actuator response speed
- User Testing: Expand trials to diverse users to refine personalized assistance • Electroencephalogram (EEG) Integration: Implement brain-
- machine interface (BMI) for control, aiding users with severe muscle weakness
- Wireless & Cloud Features: Enable remote monitoring, Aldriven adjustments, and rehabilitation progress tracking
- Clinical Application: Enhance usability for real-world medical rehabilitation

Figure References

- Sergazin, G., Zhetenbayev, N., Tursunbayeva, G., Uzbekbayev, A., Sarina, A., Nurgizat, Y., & Nussibaliyeva, A. (2024). Design, Simulation and Functional Testing of a Novel Ankle Exoskeleton with 3DoFs. Sensors, 24(19), 6160. https://doi.org/10.3390/s24196160
- 2. Zhou, B., Wang, H., Hu, F., Feng, N., Xi, H., Zhang, Z., & Tang, H. (2020). Accurate recognition of lower limb ambulation mode based on surface electromyography and motion data using machine learning. Computer Methods and Programs in Biomedicine, 193, 105486. https://doi.org/10.1016/j.cmpb.2020.105486