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Robotic Exoskeleton for Load Transportation

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iii. Abstract

a. Main objectives

This project aims to develop a software-centric enhancement module for a lower-limb robotic exoskeleton designed to assist workers in heavy load transportation tasks (>20 kg) in industrial, logistics, and construction environments. The primary objectives are to enable real-time detection of user locomotion intent (including walking, stair ascent/descent, sit-to-stand transitions, and speed variations), accurately estimate joint kinematics through multi-sensor fusion, and deliver adaptive personalized torque assistance to minimize physical effort and injury risk. To achieve this, the module will incorporate computational techniques to handle variability in user biomechanics and environmental conditions, ensuring robust performance across diverse scenarios.

b. Methods

The proposed system integrates inertial measurement units (IMUs) placed on the lower limbs and back, with data processed through a Kalman filter-based sensor fusion pipeline implemented in MATLAB to achieve robust, low-latency joint angle and velocity estimation. Locomotion mode and transition prediction are performed using machine learning models (Support Vector Machines and Long Short-Term Memory networks) trained on labeled gait datasets, targeting >90% classification accuracy and 100–200 ms predictive horizon, with performance evaluated via confusion matrices, precision, and recall. Finite state machines are incorporated for locomotion mode transitions. Data collection protocol involves attaching three mobile phones as IMUs to the hips and lower back; performing standardized tasks like walking 10 m on flat ground, climbing 10 steps, or navigating uneven surfaces at self-selected speeds; and exporting 1) accelerometer, 2) gyroscope and 3) magnetometer data as CSV files for processing. This protocol ensures reproducibility, allowing other researchers to utilize the collected data. Joint kinematics information is utilized for precise control.

c. Important results

As of December 2025, significant progress has been made: a functional data acquisition prototype using three mobile phone IMUs has been established, preliminary Kalman filtering and intention-detection algorithms have been implemented and validated on public datasets including HuGaDB and the USC-SIPI gait database. Project repository has been set up and has demonstrated real-time visualization of gait events and initial classification of basic locomotion modes with 85% accuracy and a 150 ms predictive horizon.

d. Main conclusions

This project demonstrates that automation technology, particularly real-time machine learning-based intention recognition combined with sensor fusion and finite state machines, is highly applicable and effective for next-generation powered exoskeletons. When fully realized, the proposed module has strong potential for seamless integration into existing industrial exoskeleton platforms (e.g., those developed by ExoTechHK Limited), offering high accuracy, precision, and recall in locomotion detection while enhancing safety and usability in real-world load-carrying scenarios. This work contributes to addressing global challenges in workplace ergonomics, with implications for reducing injury rates and improving productivity.

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1. Problem Description

1.1 Problem Statement

Manual load transportation in industrial, construction, and logistics settings frequently involves carrying loads exceeding 20 kg, surpassing human physiological limits and leading to high rates of low-back pain, musculoskeletal disorders (MSDs), reduced productivity, and billions in annual economic costs, worldwide. Existing assistive exoskeletons often fail to provide proactive, real-time adaptation to the user's locomotion intent or environmental changes, resulting in delayed or mismatched assistance that compromises safety and comfort. Moreover, generic assistance profiles do not account for inter-individual differences in gait asymmetry, fatigue thresholds, anthropometrics, or preferred movement patterns. These limitations are especially critical in dynamic workplaces where load magnitude, terrain, and tasks constantly vary. There remains a clear need for a lightweight, cost-effective lower-limb exoskeleton that delivers accurate intent detection, robust sensor fusion, and truly personalized adaptive control — without relying on invasive interfaces such as electromyography (EMG) or requiring extensive user training.

1.2 Project Goal

The primary goal is to develop a software-centric enhancement module for ExoTechHK Limited's existing lower-limb exoskeleton prototype — a local startup incubated at HKSTP and founded by CUHK researchers — to augment human strength and endurance during heavy load-carrying tasks (>20 kg) without invasive sensors or lengthy calibration.

The module integrates two core components:

- Data Acquisition and Processing Pipeline: Establish a robust foundation for real-time gait analysis by developing a prototype using three mobile phones as IMUs for efficient data collection, implementing a Kalman filter-based sensor fusion algorithm for accurate joint kinematics estimation, and deploying initial machine learning models (e.g., hybrid SVM + LSTM) for basic locomotion mode classification. This pipeline enables validation on public datasets and supports scalable development through an established project repository.
- Proactive Real-Time Locomotion Intent Recognition: Detect user intent (including walking, stair ascent/descent, sit-to-stand, and gait transitions such as sit-to-stand and back bending) using hip and lower-back IMU data processed via a hybrid SVM + LSTM model with multi-sensor fusion. Target performance metrics include >90% intent-detection accuracy and 100–200 ms predictive horizon, with evaluation via confusion matrices showing high precision and recall.

Being entirely software-based, the solution enables seamless integration into existing hardware prototypes, rapid deployment, and outstanding scalability across future platforms.

1.3 Significance of the Project

This project directly addresses a major occupational health crisis affecting industrial workers, logistics and construction personnel, and military operators worldwide — user groups routinely exposed to heavy manual handling and elevated injury risk. In Hong Kong alone, manual handling injuries are a leading cause of absenteeism and healthcare expenditure. By providing proactive, personalized torque assistance at the hips and knees using cooperative control strategies — in which the exoskeleton follows rather than leads the user — the system can achieve high accuracy in intent detection, with confusion matrices indicating strong precision and recall, and recent field evidence showing that such user-following approaches improve usability compared to fixed profiles (Le & Lin, 2024).

Conducted in close collaboration with ExoTechHK Limited under the HKSTP incubation programme, the project offers a clear pathway for technology transfer and commercialization. Software-centric design enables low-cost retrofitting to virtually any existing lower-limb exoskeleton worldwide and effortless upgrades across hardware generations — dramatically enhancing global adoption potential. The technology promotes safer, more productive workplaces and directly contributes to United Nations Sustainable Development Goal 8 (Decent Work and Economic Growth), while strengthening Hong Kong’s innovation ecosystem through industry–academia partnership.

Furthermore, the standardized data collection protocol employed in this project utilizes mobile phone IMUs to record gait kinematics during controlled tasks which ensures reproducibility and accessibility. This allows other researchers and developers to leverage the collected datasets for their own studies, fostering broader collaboration in biomechanics and wearable technology.

2. Results of Literature Review

2.1 Introduction

The literature review focuses on existing research related to robotic exoskeletons for back support, particularly in the context of manual material handling (MMH) and load transportation tasks. Key themes include exoskeleton designs (passive vs. active, rigid vs. flexible), actuation systems (with emphasis on cable-driven and series elastic actuators), control strategies (including intention detection, sensor fusion, and machine learning), and personalization mechanisms. The review draws from systematic reviews, empirical studies, and technical papers to identify advancements, limitations, and gaps relevant to the project's goal of developing a software-centric enhancement module for a lower-limb exoskeleton. To provide a comprehensive overview, this review incorporates recent systematic analyses from 2020–2025, highlighting post-pandemic advancements in hybrid designs, AI integration, and industrial evaluations. For instance, Pesenti et al. (2021) and subsequent updates in Kermavnar et al. (2021) and later works like those in Frontiers in Bioengineering and Biotechnology (2021) classify over 30 back-support exoskeletons, emphasizing the shift toward soft and quasi-passive systems for improved user acceptance.

2.2 Overview of Back-Support Exoskeletons for MMH

Back-support exoskeletons (BSEs) are designed to mitigate low back pain and musculoskeletal disorders (MSDs) associated with repetitive lifting, bending, and load carrying in industries such as construction, logistics, and manufacturing. A systematic review by De Looze et al. (2016) and updated analyses by Pesenti et al. (2021) classify BSEs into passive and active types. Passive BSEs, such as the Laevo or SPEXOR, rely on mechanical springs or elastic bands to store and release energy during trunk flexion-extension (TFE) motions, reducing erector spinae muscle activity by 10–40% without requiring power sources. However, they offer limited adaptability to dynamic tasks and may impose resistance during non-assisted movements.

Recent evaluations, such as Luger et al. (2023), evaluated the Laevo V2 passive exoskeleton in male workers and reported 12–19% lower erector spinae activity during symmetric and asymmetric static holding tasks. Kingma et al. (2020) further quantified that although passive exoskeletons effectively reduce peak L5/S1 moments during symmetric lifting, the moment reduction diminishes significantly when lifting involves trunk rotation or asymmetry—reinforcing the need for active, adaptive systems in real-world industrial settings where perfectly symmetric lifts are rare.

Active BSEs, like the SuitX BackX or Ekso Bionics' EksoVest, incorporate powered actuators to provide on-demand assistance, achieving up to 50% reduction in metabolic cost and lumbar compression forces. For instance, the SIAT-WEXv2 active lumbar exoskeleton developed by Ji et al. (2020) reduced peak lumbar moments by 25–35% during repetitive box lifting of 15–25 kg loads, confirming the effectiveness of combined hip and knee actuation in scenarios directly comparable to the >20 kg transportation tasks targeted in this project. Golabchi et al. (2023) highlight their potential in construction, where workers handle loads exceeding 20 kg, but note challenges in portability, weight (often >5 kg), and user comfort. A comprehensive review by Kermavnar et al. (2021) of 28 BSEs for MMH tasks emphasizes that while active systems excel in heavy-load scenarios, they often suffer from rigid structures that restrict natural range of motion (RoM) in sagittal, frontal, and transverse planes, leading to misalignment and discomfort. However, even some passive devices can alter natural kinematics; Simon et al. (2021) observed slight forward tilt of the pelvis and reduced lumbar flexion when using a lift-assistive exoskeleton, underscoring the importance of compliant actuation designs that preserve physiological joint trajectories. Pesenti et al. (2021) reviews 23 studies and 12 devices, with soft robotic suits like the HeroWear Apex or APEX demonstrating textile-based designs that improve flexibility but provide lower torque (<30 N·m) compared to rigid counterparts. Long-term field evaluations, such as those by Luger et al. (2023), show that BSE adoption increases with user acceptance, but dropout rates are high due to fit issues and lack of personalization. In load transportation contexts, studies such as Yandell et al. (2020) and updated by Dai & Novak (2021) on the HeroWear Apex exosuit indicate reductions in back forces during lifting and bending, with metabolic cost decreases of 7.9–23% but highlight trade-offs in comfort for overhead tasks.

Categorization from recent reviews divides devices into powered, unpowered, and quasi-passive. Powered types, such as the Cray X, reduce erector spinae activity by 16–37.8% in asymmetric lifting, while unpowered ones like VT-LOWE use carbon fiber beams for 31.5% peak muscle reduction. Quasi-passive hybrids combine springs with minimal actuators for 36.92% activity reduction, offering energy efficiency. These classifications reveal a trend toward hybrid systems to balance power and portability, with industrial applications showing 20–50% strain reductions but limited by high costs and weight.

Further evidence from both passive and quasi-passive systems reinforces their effectiveness in controlled lifting and carrying tasks, while also highlighting remaining adoption barriers. For instance, the SPEXOR passive spinal exoskeleton reduced net metabolic cost by 18% (range 11–25%) during symmetric repetitive lifting (Baltrusch et al., 2020). More recent quasi-passive designs that incorporate compact variable gravity compensation modules have achieved comparable reductions in erector spinae activity with noticeably improved wearer comfort and reduced resistive torque during non-assisted movements (Song et al., 2024). Despite these physiological benefits, long-term field adoption remains constrained by limited adaptability to highly dynamic or asymmetric tasks and by persistent user-acceptance challenges, including gender-specific differences in perceived comfort and usability (Babič et al., 2021; Luger et al., 2023).

2.3 Actuation Systems: Focus on Cable-Driven and Series Elastic Actuators

Actuation design is critical for efficient torque delivery while ensuring safety and ergonomics. Traditional rigid actuators transmit force via linkages but can cause parasitic forces and limit RoM. Cable-driven systems address this by using flexible transmissions, allowing off-board or on-board placement for portability. Chen et al. (2019) and Li et al. (2022) review and demonstrate cable-driven exoskeletons, noting their advantages in reducing structural weight and enabling multi-DoF compensation for misalignment. Recent advancements include Li et al. (2022)'s cable-driven asymmetric back exosuit, providing 38% muscle activity reduction in lifting, and Ding et al. (2023)'s spring-cable-differential for passive assistance.

Series elastic actuators (SEAs) integrate compliant elements to enhance shock tolerance, force control, and human-exoskeleton interaction safety. Pratt and Williamson (1995) pioneered SEAs, and recent applications in BSEs include the work by Hyun et al. (2020). A key advancement is the cable-driven series elastic actuation (CSEA) system proposed by Liao et al. (2024), which use a torsion spring-support beam mechanism with deflection constraints to operate in multiple statuses: SEA mode for compliant, low-torque assistance and conventional stiff actuator (CSA) mode for high-torque output (>50 N·m). This design enlarges the moment arm of cable force, reducing lumbar compression and cable force demand by up to 50% compared to parallel cable placements in conventional systems (e.g., Chen et al., 2019). Bench and human tests in Liao et al. (2024) validated a 20–30% reduction in erector spinae EMG during TFE, with stable torque control despite status transitions.

Other CSEA variants include those characterized in Poliero et al. (2022) and Liao et al. (2024), achieving high compliance but noting trade-offs in stiffness selection. Ding et al. (2024) introduced a differential SEA with cable routing for precise force control. In soft exoskeletons, twisted string actuators (TSAs) from Xiloyannis et al. (2019) enable lightweight designs with high force density, reducing system weight by up to 80% in some cases.

Comparative analysis shows that cable-driven SEAs excel in flexibility but require careful routing and low-friction sheathing to reduce transmission losses (Poliero et al., 2022; Liao et al., 2024). Careful Bowden cable routing and pre-tensioning, as successfully demonstrated in upper-limb cable-driven systems by Tsai et al. (2019), will be adopted to minimize friction and hysteresis in the lower-limb prototype. For load transportation, these systems typically deliver 20–50 N·m of torque — sufficient for assisting with loads greater than 20 kg — although challenges in battery life and heat dissipation remain.

2.4 Control Strategies: Intention Detection, Sensor Fusion, and Machine Learning

Effective BSE control requires real-time detection of user intent and environmental adaptation. Traditional methods use EMG or IMUs for gait event detection, but they struggle with transitions. Machine learning has emerged for intention prediction: Novak and Riener (2015) reviews ML-based locomotion mode classification using SVMs or LSTM networks, achieving >90% accuracy. Recent applications include Jiang et al. (2024)'s EMG-based loading recognition for lumbar exoskeletons. Earlier hip-exoskeleton work by Chen et al. (2018) also showed that simple kinematic thresholds on hip flexion angle and angular velocity can reliably detect the onset of lifting within 150–200 ms, offering a lightweight, non-ML baseline that remains relevant for fallback strategies in noisy industrial environments.

Sensor fusion, often via Kalman filters, integrates IMU data for accurate joint kinematics estimation with low latency (<200 ms). Lazzaroni et al. (2022) improved efficacy with accelerometer-based control, achieving better synchronization during manual handling. Adaptive control, as in Toxiri et al. (2018), uses finite state machines to modulate assistance based on trunk angle, reducing user effort by 25%. Expanding on this, Poliero et al. (2022) compared active and passive BSEs in dynamic tasks, showing active systems reduce erector spinae activity by 28% via accelerometer signals.

Personalization is a growing focus: Kermavnar et al. (2021) and Luger et al. (2023) highlight that generic assistance profiles underperform across diverse users and call for trial-based or adaptive tuning. Post-2020 advancements include reinforcement learning (RL) for control optimization, as in Luo et al. (2023), reducing metabolic cost by 13–24% in walking/stairs, and online RL approaches for user preference in timing/torque. For load transportation, Xiang et al. (2023) dynamically evaluated multiple back-support exoskeletons and reported 19–69% reductions in peak back-muscle activity, 300–672 N reductions in low-back compressive force) across various manual handling tasks and highlights needs for ML in asymmetric tasks.

2.5 Evaluation Studies and User Acceptance

Empirical studies provide quantitative insights. For passive BSEs, van Sluijs et al. (2023) reported physiological benefits in lifting/leaning, while Alemi et al. (2020) reported 4–13% reductions in energy expenditure during repetitive lifting with two passive back-support exoskeletons. Qu et al. (2021) evaluated a commercial passive exoskeleton in real industrial lifting tasks and reported 18–32% lower back-muscle activity (iEMG) and significantly improved subjective comfort scores, while oxygen consumption remained unchanged, providing real-world validation of the metabolic benefits claimed in laboratory settings. Active systems, per Schwartz et al. (2023), reduce activity during lifting, with subjective comfort improvements. Quasi-passive systems, like Jamšek et al. (2020), use Gaussian mixture models for periodic assistance. User acceptance studies (e.g., Refai et al., 2023) show soft actuated BSEs influence multimodal measurements positively, but gender differences exist in overhead tasks (Nussbaum & Madinei, 2023).

2.6 Gaps and Implications for the Project

Tröster et al. (2022) used a detailed musculoskeletal model to compare stoop and squat lifting with and without back-support exoskeletons, concluding that assistance magnitude must be adjusted dynamically according to lifting technique—further motivating the adaptive control strategy pursued in this project. Despite advancements, gaps persist in portable, flexible BSEs with efficient actuation for load transportation. Rigid systems limit RoM, while cable-driven SEAs often require high forces. ML and sensor fusion show promise for proactive assistance, but few studies combine them with personalization for real-time adaptation, as noted in Lin et al.'s (2025) review of locomotion exoskeletons. The project addresses these by enhancing an existing prototype with MATLAB-based algorithms for IMU fusion, SVM/LSTM intention detection, and trial-based fine-tuning, targeting >90% accuracy and 30–50% strain reduction.

The present work directly addresses four critical gaps repeatedly identified in recent reviews (Kermavnar et al., 2021; Pesenti et al., 2021; Lin et al., 2025; Tröster et al., 2022):

- Lack of real-time personalization and user-specific adaptation.
- Insufficient handling of asymmetric and highly dynamic load-transportation tasks.
- Delayed or reactive assistance onset in active/quasi-passive systems.
- Limited transferability and rapid prototyping of advanced control on existing hardware.

By closing these gaps in a single integrated, software-centric framework, the project moves beyond incremental hardware improvements and provides a scalable pathway toward truly adaptive, user-accepted back-support assistance in real-world manual material handling and load-transportation scenarios.

2.7 Summary Table of Representative Back-Support Exoskeletons

Device / Study	Type	Assistive Torque (N·m)	Reported Metabolic / EMG Reduction	Key Limitation
Laevo V2 (Luger et al., 2023)	Passive	~35–40	12–19% erector spinae EMG (static holding)	Resistance in extension; poor asymmetry support
SPEXOR (Baltrusch et al., 2020)	Passive	~40	11–25% net metabolic cost (repetitive lifting)	Fixed assistance profile; added hip stiffness
HeroWear Apex / APEX 2 (2023–24)	Soft quasi-passive	25–35	7.9–23% metabolic, ~20–30% back force	Lower torque than rigid; limited overhead support
SuitX BackX (commercial)	Active	30–60	Up to 50% lumbar compression force	Weight >7 kg; rigid structure restricts RoM
Cray X (Steinbeiss et al., 2022)	Active	50–80	16–37.8% erector spinae EMG (asymmetric lifting)	High power consumption; bulky battery
SIAT-WEXv2 (Ji et al., 2020)	Active (hip+knee)	~60 (combined)	25–35% peak lumbar moment (15–25 kg lifting)	Complex mechanics; >5 kg total weight
VT-LOWE (carbon-fiber) (2023)	Passive	~45	31.5% peak back-muscle activity	No dynamic adaptation; fixed spring stiffness
Liao et al. CSEA (2024)	Quasi-passive/active hybrid	>50 (CSA mode), variable SEA	20–30% erector spinae EMG (bench + human trials)	Mode-switching complexity; still prototype-stage
Auxivo LiftSuit (2024)	Quasi-passive	30–45	15–28% metabolic, ~35% EMG in dynamic lifting	Limited torque customization without add-ons
Hyundai/German Bionic Apogee	Active	50–75	20–40% back load reduction in industrial trials	Cost and maintenance; rigid shoulder harness

3. Approach to the Problem

3.1 Proposed Methodologies

The project will employ a multidisciplinary approach combining mechanical design, signal processing, and machine learning, primarily using MATLAB for algorithm development. Key methodologies include:

3.2 Intention Detection Algorithm

Develop a real-time algorithm in MATLAB to classify user locomotion modes (e.g., walking, stair ascent/descent) and transitions (e.g., sit-to-stand), incorporating speed variations and multi-motion transitions (e.g., walking to sitting) based on hip and back kinematics. Features extracted from IMU signals will enable predictive control to anticipate user actions 100-200 ms in advance.

To expand this, the algorithm will use a hybrid SVM + LSTM framework: SVM (with RBF kernel) for initial mode classification due to its efficiency in high-dimensional spaces, and LSTM (2 layers with 128 hidden units each) for temporal sequence prediction to handle transitions. Feature extraction will include time-domain (mean, variance) and frequency-domain (FFT peaks) metrics from acceleration and angular velocity data. Training will involve augmented datasets with noise injection for robustness in noisy industrial environments, using approximately 5000 samples–80% for training, 20% for testing/validation.

Example Pseudocode for intention detection:

```
% Load IMU data
data = loadIMUData();

% Feature extraction e.g.[mean(acc), var(gyro), etc.]
features = extractFeatures(data);

% SVM classification for modes
mode = svmClassify(features, trainedSVMModel);

% LSTM for transition prediction
sequence = preprocessForLSTM(data);
predictedTransition = lstmPredict(sequence, trainedLSTMNet);

% Combine for intent
intent = fuseModeAndTransition(mode, predictedTransition);
```

3.3 Multi-Sensor Data Processing Pipeline

Implement a Kalman filter (via MATLAB's imufilter function) to fuse accelerometer and gyroscope data from IMUs placed at the hips and back. This will provide accurate, low-latency estimates of joint angles and velocities, reducing noise and drift for robust kinematics tracking. Expansion includes an Extended Kalman filter (EKF) variant for nonlinear dynamics in load-carrying, incorporating magnetometer data for heading correction and absolute angle determination. The pipeline will handle sensor biases via online calibration and use complementary filtering for short-term accuracy. Validation will use RMSE metrics against ground-truth motion capture data, targeting <5° error.

Example MATLAB code snippet for Kalman-based fusion:

```
% Initialize IMU filter
```

```
f = imufilter('SampleRate', 100, 'AccelerometerNoise', 0.01,
'GyroscopeNoise', 0.01);

% Fuse data
[orientation, angVel] = f(accData, gyroData);

% Estimate joint angles by custom quaternions function
hipAngle = computeJointAngle(orientation);

% Display
plot(hipAngle);
```

3.4 Machine Learning Model Training and Deployment

Utilize MATLAB's Statistics and Machine Learning Toolbox for Support Vector Machine (SVM) models and Deep Learning Toolbox for Long Short-Term Memory (LSTM) networks. Models will be trained on labelled datasets of locomotion data to achieve >90% accuracy in dynamic terrain recognition (e.g., flat ground vs. stairs), with evaluation using confusion matrices, precision, and recall. Post-trial fine-tuning will use transfer learning to adapt pre-trained models to individual user data, optimizing hyperparameters via cross-validation. Expansion involves ensemble methods (e.g., SVM + LSTM) for improved accuracy, with hyperparameter tuning using Bayesian optimization. Datasets like HuGaDB will be augmented with synthetic variations (e.g., via physics simulations). Deployment will use MATLAB Coder for real-time execution on embedded systems.

Training workflow:

1. Preprocess data (normalize, segment into windows).
2. Train base models on public datasets.
3. Fine-tune with user trial data: minimize loss = cross – entropy + regularization.
4. Evaluate with confusion matrices and F1-scores.

3.5 System Integration and Control

Translate model outputs (predicted intents) into torque commands for exoskeleton actuators using a finite state machine controller. The system architecture includes gait event detection (heel strike, toe-off), intention recognition via ML, and reference signal generation for terrain-adaptive control. The architecture can be visualized as follows:

- **Input Layer**: IMU sensors collect raw data (acceleration, angular velocity).
- **Processing Layer**: Kalman filter fuses data for kinematics; ML models classify intents. Parallel processing for low latency (<50 ms).
- **Control Layer**: Finite state machine generates torque profiles. Use PID controllers with adaptive gains.
- **Output Layer**: Actuators deliver assistance to hips/knees. Safety checks for torque limits.

Integration with hardware (ExoTechHK frame) will use ROS Toolbox for simulation before real deployment. Potential issues like sensor drift will be addressed with periodic resets.

The modular mechanical design philosophy adopted in this project draws inspiration from successful rehabilitation exoskeletons such as the one presented by dos Santos et al. (2017), which demonstrated that segmenting the structure into independent thigh and shank modules simplifies alignment and reduces migration during prolonged use.

3.6 List of MATLAB Libraries to be Used

Optional libraries included for hardware integration and advanced features:

Library	Description
MATLAB	Core computing environment for scripting and simulation.
Signal Processing Toolbox	For filtering and signal processing of IMU data.
Statistics and Machine Learning Toolbox	For feature extraction and machine learning model training (e.g., SVM).
Sensor Fusion and Tracking Toolbox	For IMU data fusion and pose estimation using Kalman filters.
Deep Learning Toolbox	For models like LSTM/CNN in intention detection.
Optimization Toolbox	For hyperparameter tuning via Bayesian methods.
Control System Toolbox	For PID and adaptive controllers in torque generation.
MATLAB Support Package for Arduino (Optional)	For hardware connections to Arduino-based actuators.
ROS Toolbox (Optional)	For communication with ROS systems in simulation or integration.

This approach ensures scalability, with simulations validating 85-95% accuracy before hardware tests.

4. Current Progress

4.1 Data Acquisition Prototype

As of December 2025, the project has achieved several key milestones aligned with the proposed methodologies. A functional data acquisition prototype has been developed using three mobile phones as IMUs (leveraging built-in accelerometers, gyroscopes, and magnetometers) to simulate sensor placement on the lower limbs and back. This prototype enables real-time data collection. The data collection protocol involves attaching the phones to the hips and lower back; performing standardized tasks like walking 10 m on flat ground, climbing 10 steps, or navigating uneven surfaces at self-selected speeds; and exporting data as CSV files. This ensures reproducibility, allowing other researchers to use the collected data. Testing has included preliminary simulations to verify data integrity.

4.2 Sensor Fusion and Intention-Detection Algorithms

Preliminary implementations of the Kalman filter-based sensor fusion pipeline have been completed using the Sensor Fusion and Tracking Toolbox. This has been validated on public gait datasets (e.g., from the HuGaDB database and USC-SIPI gait dataset), demonstrating low-latency joint angle estimation with root mean square errors (RMSE) below 5° for basic walking scenarios. Additionally, initial intention-detection algorithms, including a basic SVM classifier for locomotion modes (walking vs. standing), have been coded and tested, achieving approximately 85% accuracy on labeled data with a predictive horizon of 150 ms, evaluated via confusion matrices showing good precision and recall.

Confusion matrix for binary classification (walking vs. standing) on the HuGaDB dataset:

	Predicted Walking	**Predicted Standing**
Actual Walking	420 (True Positives)	80 (False Negatives)
Actual Standing	70 (False Positives)	430 (True Negatives)

This matrix indicates high true positives and negatives, with precision of 0.86 for walking and recall of 0.84 for standing.

4.3 Visualization Tools and Repository Setup

Real-time visualization tools have been integrated, allowing for live plotting of gait events (e.g., heel strike detection) and kinematic parameters in MATLAB. The project repository has been established on GitHub, containing initial scripts for data acquisition, filtering, and classification, along with documentation and sample datasets. These accomplishments provide a solid foundation, confirming the feasibility of the core algorithms in a simulated environment.

5. List of Remaining Tasks

Based on the current progress, the following tasks remain to complete:

- Intention Detection Algorithm: Expand the preliminary SVM to include LSTM for multi-mode transitions and speed variations; achieve >90% accuracy through further training and ensemble methods.
- Machine Learning Models: Train and deploy full SVM/LSTM models for terrain recognition; generate confusion matrices, F1-scores, and deployment scripts for embedded systems.
- Control System Prototype: Integrate software with ExoTechHK frame for torque control and include safety interlocks.
- Testing and Validation: Conduct bench tests, ethical user trials with torque limits to prevent over-assistance, and performance evaluations (e.g., accuracy, confusion matrix, precision, recall).
- Project Report and Presentation: Compile final documentation, including results analysis, future work, PowerPoint slides, and video demonstration; update GitHub with all assets. Include comparative analysis with literature benchmarks.

Future work beyond FYP Project:

- Personalization Module: Implement an adaptive fine-tuning via a 3–5 minute initial free-walking calibration phase; collect individual gait characteristics and automatically optimize assistance parameters using transfer learning combined with lightweight reinforcement learning (PPO or SAC);
- Quantitative Injury-Risk Assessment: Integrate the ergonomic risk-score framework proposed by Zelik et al. (2022) into user trials to objectively quantify reduction in lumbar and lower-limb injury risk during load-carrying and prolonged walking tasks.

6. Work Schedule for Completion of Remaining Tasks

The list of remaining tasks spans January 2026 to May 2026 (5 months), divided into phases for iterative development and milestones. The timeline assumes monthly advisor reviews and buffers for unexpected delays like hardware procurement. Progress will be tracked via Email and GitHub for task management.

Phase	Duration	Key Activities	Milestones
ML Training & Simulation Integration	Jan – Feb 2026 (2 months)	Train/deploy ML models; build Simulink HIL controller; iterate on virtual tests for locomotion modes, including load simulations.	Validated models (≥90% accuracy); full simulation demo showing assisted walking with personalization.
Hardware Integration & Testing	Mar – Apr 15, 2026 (1.5 months)	Integrate software-hardware; conduct bench and limited treadmill tests (5-10 trials), with ethical approvals.	Test logs with latency/error metrics
Optimization, Documentation & Finalization	Apr 16 – May, 2026 (1.5 months)	Refine based on tests; compile report; prepare presentation	Submitted report; presentation; archived repo with all assets.

To ensure robustness, risks are assessed with mitigations.

Risk	Likelihood	Impact	Mitigation Strategy
Hardware integration delays (e.g., actuator compatibility with ExoTechHK frame)	Medium	High	Use modular off-shelf parts; parallel software dev; early prototype loan from collaborators.
ML model underperformance (<85% accuracy)	Low	Medium	Fallback to hybrid rule-based/ML; augment with ExoTechHK datasets; iterative cross-validation and RL tuning.
Trial delays	Medium	High	Use simulated/public data as interim; limit to 5-10 ethical volunteers; secure IRB early.
Budget overrun	Low	Low	University funding; seek HKSTP supplements.

7. References

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