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Sensor-Driven Strain Detection and Deep Learning Evaluation of Passive Exoskeletons in Industrial Tasks

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Abstract— **Work-related musculoskeletal disorders (WMSDs) persist in material-handling jobs where lifting, twisting, and carrying induce high, localized muscle demands. This paper presents a sensor-driven framework that (i) detects biomechanical strain from surface electromyography (sEMG) and (ii) quantifies the impact of a passive back-support exoskeleton during industrially relevant tasks. With data from 20 participants performing standardized tasks with and without the device, we introduce a data-driven strain labeling method that replaces ad-hoc thresholds with piecewise linear regression to identify individualized strain onset. A compact deep neural network handles severe class imbalance via SMOTE and decision-threshold optimization, yielding 83.5% overall accuracy and a macro-averaged F1-score of 0.70 for binary strain classification. Muscle-specific analyses reveal significant reductions in biceps and oblique activation ($p < 0.001$) alongside compensatory increases in erector spinae and lower-limb activity, indicating load redistribution rather than uniform offloading. The result is a scalable, real-time approach that captures both when strain begins and how effort shifts across muscle groups, capabilities that traditional peak-sEMG or subjective assessments miss. By uniting wearable sensing, automated strain onset detection, and imbalance-aware learning, this work advances objective, continuous, and human-centered ergonomic monitoring and provides actionable evidence for the deployment of passive exoskeletons in smart industrial environments.**

I. INTRODUCTION

Work-related musculoskeletal disorders (WMSDs) remain a leading cause of occupational injury worldwide, contributing to lost workdays, reduced productivity, and increased healthcare costs [1]. Physically demanding tasks such as lifting, carrying, bending, and twisting impose significant biomechanical strain on the musculoskeletal system [2], [3], [4]. These repetitive and force-intensive actions accelerate fatigue, cause localized muscle overuse, and increase the risk of long-term injuries. The prevalence of WMSDs underscores the urgent need for effective interventions that mitigate strain and enhance worker safety in manufacturing and logistics environments [5], [6], [7].

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Passive exoskeletons have emerged as a promising class of assistive technologies designed to reduce muscle loading by providing mechanical support without external power [8], [9], [10]. Compared to active systems, passive exoskeletons are lightweight, energy-efficient, and suitable for continuous use in occupational settings [11], [8], [12]. While prior studies suggest that exoskeletons alleviate strain on targeted muscle groups, the broader physiological effects remain poorly characterized, particularly the redistribution of muscular effort across multiple regions [13], [14]. Also, most evaluations have relied on subjective feedback or simple sEMG peak analysis, which fail to capture the onset and progression of muscular strain [15], [16], [17].

Advances in wearable sensing and machine learning now enable real-time analysis of neuromuscular activity with greater precision [18], [19]. Surface electromyography (sEMG), when combined with signal processing and predictive modeling, provides quantitative insight into muscle activation patterns during industrial tasks [20], [21]. These methods can support automated classification of strain events and assessment of exoskeleton efficacy [22]. However, challenges such as severe class imbalance between strain and non-strain events and the lack of standardized approaches for strain onset detection continue to limit robust ergonomic assessment [23].

In this work, we present a sensor-driven framework for evaluating passive exoskeletons during repetitive industrial tasks. Our approach integrates sEMG-based feature extraction, automated strain onset labeling via piecewise linear regression, and deep learning classification optimized with SMOTE-based augmentation and threshold tuning. The framework was validated in an experiment with twenty participants performing lifting, carrying, and twisting tasks with and without a passive back-support exoskeleton. The main contributions of this study are:

- A data-driven framework for real-time strain detection that combines sEMG, RMS-based feature extraction, and deep learning.
- A novel strain onset detection method using piecewise linear regression to replace arbitrary thresholds with individualized cutoffs.
- Experimental validation with 20 participants, demonstrating significant reductions in biceps and oblique activity alongside compensatory increases in erector spinae and lower-limb muscles, highlighting redistribution effects.

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Together, these contributions advance the understanding of exoskeleton efficacy and establish a scalable approach to sensor-driven ergonomic risk detection in human-centered industrial systems.

II. Methodology

A. Experimental Protocol and Data Acquisition

This study was approved by the Institutional Review Board (IRB protocol No.: 23-12-2086, approved on 19 December 2023), and informed consent was obtained from all participants. They were informed they could withdraw at any time without penalty; all chose to complete the study. After the experimental tasks, participants completed a post-study survey to provide feedback on their experience.

In this study, we used the *Ottobock BackX* passive back-support exoskeleton intended for industrial applications (see Fig. 1). The device supports the chest and thighs to counteract gravity-induced loads on the lower back, reducing effort during lifting, bending, and reaching; the front- and rear-side layouts are shown in Fig. 1(a) and Fig. 1(b), respectively. The fit was manually adjusted to each participant's anthropometrics. Before data collection, participants received an orientation to the passive exoskeleton and provided written informed consent.

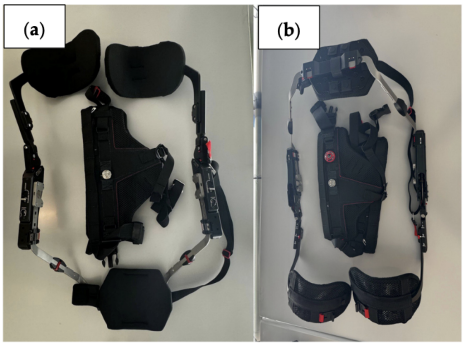

Fig. 1. Ottobock BackX passive back-support exoskeleton used in this study: (a) front-side layout with chest pads; (b) rear-side layout showing waist and thigh interfaces.

Twenty participants (mean age 20.9 ± 3.2 years; mean weight 65.9 ± 11.6 kg; mean height 169.2 ± 11.2 cm; 12 males, 8 females) performed three structured, industrially relevant tasks of lifting, twisting, and carrying, both with and without a passive back-support exoskeleton. These tasks were designed to reflect common material-handling activities where back support is critical:

- *Lifting:* Lifting a 4.5 kg box from the ground to a 76-cm table, 16 repetitions within three minutes.
- *Twisting:* Lifting the same box from the ground to a 76-cm table positioned laterally (left or right), 8 repetitions per side within three minutes.
- *Carrying:* Carrying the box along a designated path, placing it on a table, and repeating three times within three minutes.

Figure 2 illustrates the experimental setup. Each participant completed the full set of tasks under both conditions: without the exoskeleton first, followed by the same tasks with the exoskeleton after a short rest period. Each session lasted approximately 30 minutes. Signals from sEMG sensors were recorded from eight sites, including bilateral erector spinae, obliques, quadriceps, and hamstrings. Sensors were placed on the muscle belly following SENIAM guidelines to reduce cross-talk and ensure stable signals during movement. Wireless sEMG sensors (Delsys Trigno) recorded signals at a sampling rate of 1259.26 Hz, synchronized across all channels. Data were streamed in real time and stored for offline preprocessing and feature extraction.

Fig. 2. Experimental setup showing: (top) lifting and placing tasks with the passive back-support exoskeleton; (bottom left) wireless sEMG sensor placement on back and legs; (bottom middle) data acquisition system; (bottom right) carrying and twisting tasks.

B. Signal Processing and Feature Extraction

Raw sEMG signals were first standardized using z-score normalization to mitigate inter-subject variability. Then, root mean square (RMS) values were computed over sliding windows of 0.5 seconds with a 0.05-second step to capture short-term signal energy:

$$\mathrm{RMS}(t) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} Z_i^2} \tag{1}$$

where $N = 629$ samples per window, and Z_i represents standardized sEMG values. Each window was assigned a midpoint timestamp, and RMS values across all muscles formed the feature set.The RMS of the EMG signal was used as a feature for modeling strain because it provides a reliable estimate of muscle activation amplitude and is widely employed as an indicator of neuromuscular effort during occupational tasks [24], [25].

C. Automated Strain Labeling and Model Optimization

To avoid arbitrary thresholding for muscular strain detection, we applied piecewise linear regression to each participant's RMS trajectory derived from the sEMG signal [26]. The onset of strain was defined as the breakpoint t^* that minimized the residual sum of squares across two linear segments:

$$t^* = \arg\min_t \left[\sum_{k=1}^{t}(RMS_k - R\hat{M}S_k^{(1)})^2 + \sum_{k=t+1}^{T}(RMS_k - R\hat{M}S_k^{(2)})^2\right], \quad (2)$$

where $R\hat{M}S^{(1)}$ and $R\hat{M}S^{(2)}$ represent the optimal linear fits before and after t, respectively. Timepoints after t^* were labeled as strain ($y = 1$), while earlier points were labeled as no strain ($y = 0$). This data-driven approach avoids heuristic cutoffs and accounts for individual task progression [27].

Because the resulting dataset exhibited class imbalance between strain and non-strain samples, we applied the Synthetic Minority Oversampling Technique (SMOTE) to augment minority class samples during training [28]. A feedforward neural network with dropout regularization was then trained to minimize the binary cross-entropy (BCE) loss [29]:

$$\mathcal{L}_{\text{BCE}} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right], \quad (3)$$

where N is the number of samples, $y_i \in \{0,1\}$ is the ground-truth label, and $\hat{y}_i \in (0,1)$ is the predicted probability of strain for sample i. Finally, probabilistic outputs were converted into binary class decisions using a tunable decision threshold $\tau \in (0,1)$, which was optimized during validation to maximize class sensitivity:

$$\hat{y}_i^{\text{bin}} = \begin{cases} 1, & \text{if } \hat{y}_i \geq \tau, \\ 0, & \text{otherwise.} \end{cases} \quad (4)$$

D. *Statistical Analysis of Muscle Activation*

To evaluate the biomechanical effect of exoskeleton use, we compared the RMS values of each muscle group across the two conditions (Exo vs. NoExo). Group comparisons were conducted using Welch's t-test, which accounts for unequal variances between samples. Analyses were performed for the full dataset as well as for strain-only subsets, allowing us to isolate muscular redistribution effects specifically during high-exertion periods.

III. Results and Findings

A. *Strain Detection Model Performance*

A major challenge in detecting muscular strain is the severe class imbalance between *No Strain* and *Strain* cases. Prior to resampling, the training set contained 21,710 no-strain windows compared to only 3,425 strain windows. To address this imbalance and improve sensitivity to strain events, SMOTE was applied, balancing both classes to 21,710 windows each. The final feedforward neural network consisted of an input layer with 8 features, followed by three hidden layers of 32, 16, and 8 units with ReLU activations and dropout (0.3, 0.2, 0.2), and a sigmoid output neuron for binary classification. Training employed the Adam optimizer with binary cross-entropy loss, while monitoring accuracy, precision, recall, and F1-score. Figure 3 shows the relationship between precision, recall, and F1-score across varying decision thresholds. Based on this analysis, an operating point of $\tau = 0.6$ was selected, as it maximized the F1-score for the strain class while prioritizing recall, which is critical in safety applications.

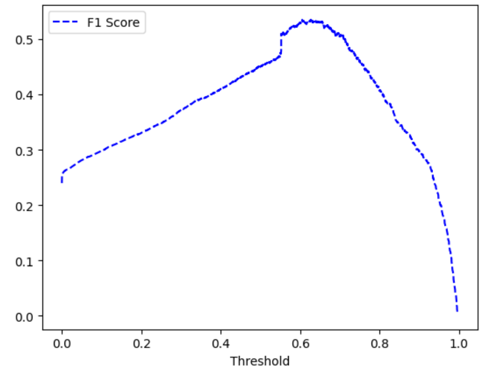

Fig. 3. F1-score and precision–recall as a function of decision threshold. The chosen operating point $\tau = 0.6$ maximized F1 for strain while limiting false negatives.

Figure 4 presents the confusion matrix on the held-out test set at $\tau = 0.6$, illustrating classification outcomes. Performance metrics at this threshold were calcuated based on the confusion matrix. The model achieved an overall accuracy of 83.5% and a macro-averaged F1-score of 0.70. For the *No Strain* class, detection was highly reliable (precision = 0.94, recall = 0.87, F1 = 0.90). For the *Strain* class, precision was lower (0.43) but recall improved to 0.62, yielding an F1 of 0.51. These results reflect the expected tradeoff in safety-critical ergonomic monitoring: higher recall for strain is prioritized to avoid missed detections, even at the expense of precision. The combination of SMOTE augmentation and threshold optimization improved sensitivity to strain events, confirming potential utility of the modeling approach in real-time ergonomic assessment.

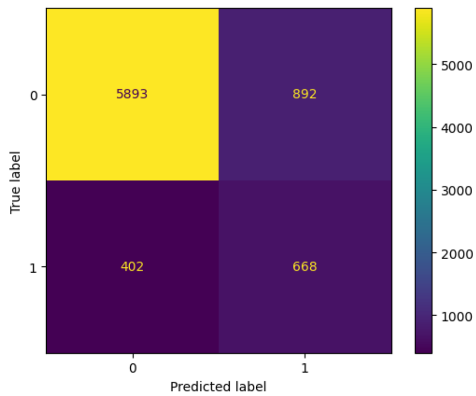

Fig. 4. Confusion matrix on the test set at $\tau = 0.6$.

B. *Effect of the Exoskeleton on Muscle Activation*

To assess the overall effect of the exoskeleton, RMS values from all eight muscle groups were compared between Exo and NoExo conditions. The mean standardized RMS was lower with the exoskeleton (-0.156) compared to without (0.137).

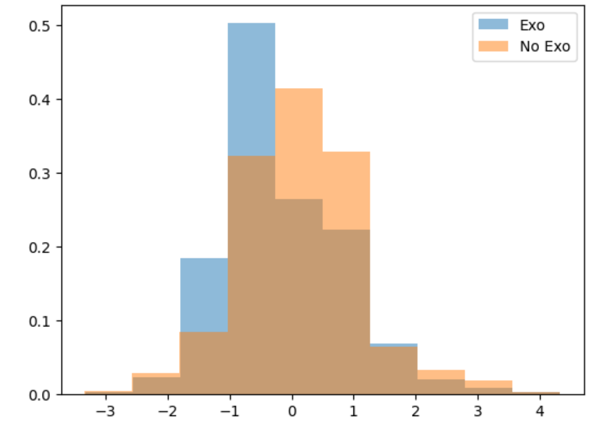

Fig. 5. Histogram of standardized RMS values across all muscles under Exo and NoExo conditions.

A Welch's two-sample t-test confirmed this reduction was highly significant ($t = -82.8$, $p < 0.001$). Figures 5 and 6 illustrate this effect, showing a distributional shift and lower median activation under the Exo condition. These results demonstrate that the exoskeleton significantly reduces overall muscular effort across industrial tasks.

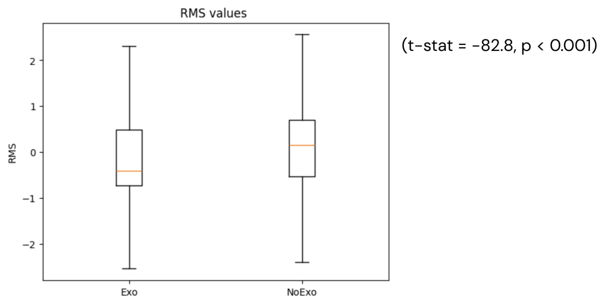

Fig. 6. Boxplot of standardized RMS values across all muscles under Exo and NoExo conditions.

C. Effect of Exoskeleton Under Strain Conditions

To assess the exoskeleton's effect during strain events, RMS values were compared between Exo and NoExo conditions. The mean standardized RMS was lower with the exoskeleton (-0.310) than without (0.059). A Welch's two-sample t-test confirmed this reduction was highly significant ($t = -37.9$, $p < 0.001$). Figures 7 and 8 illustrate this effect, showing consistently reduced activation when the exoskeleton was worn. These findings indicate that the exoskeleton is particularly effective in alleviating muscular effort during high-demand periods, reinforcing its potential as a practical ergonomic intervention in industrial tasks.

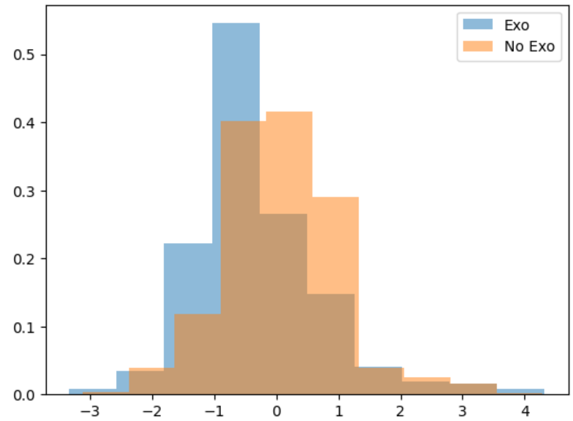

Fig. 7. Histogram of standardized RMS values under strain conditions for Exo and NoExo.

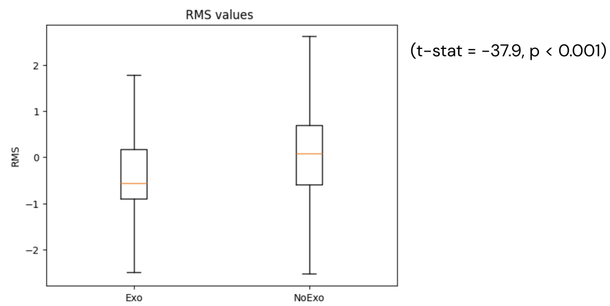

Fig. 8. Boxplot of standardized RMS values under strain conditions for Exo and NoExo.

D. Muscle-Specific Activation Redistribution

A detailed analysis of individual muscle channels confirmed distinct patterns of load redistribution when the exoskeleton was worn during strain conditions. The biceps (Left: $t = -50.7$, $p < 0.001$; Right: $t = -58.6$, $p < 0.001$) and obliques (Right: $t = -64.3$, $p < 0.001$; Left: $t = -5.4$, $p < 0.001$) exhibited significantly reduced RMS values, demonstrating effective offloading of upper-limb and trunk rotation muscles. Similarly, the right leg showed a significant reduction in activation ($t = -13.7$, $p < 0.001$). In contrast, compensatory increases were observed in the left erector spinae ($t = 27.8$, $p < 0.001$) and left leg ($t = 14.4$, $p < 0.001$), while the right erector spinae showed no significant difference ($p = 0.6$). These results highlight that the exoskeleton does not uniformly reduce strain across all muscles but instead redistributes muscular effort, decreasing demand on the biceps and obliques while shifting some load to postural stabilizers in the back and legs.

IV. Discussion and Conclusion

This study provides new insights into how passive exoskeletons alter biomechanical load pathways during physically demanding tasks. The primary observation is a redistribution of muscular effort, substantial reductions in biceps and obliques, muscles heavily engaged during repetitive lifting and trunk rotation, occur alongside compensatory increases in the erector spinae and lower limbs. These patterns are consistent with the design intent of passive back-support exoskeletons, which offload the trunk and upper body by transferring part of the workload to the lower extremities. Converging evidence supports this interpretation. Ahn *et al.* [16] reported reduced trapezius and erector spinae activity paired with greater lower-limb engagement, while Garcia *et al.* [30] found decreased erector spinae demand but elevated knee flexion and vastus lateralis activation during inclined load carrying. Together, these findings underscore the need for muscle-specific evaluation, as overall RMS reductions can obscure localized increases in postural demand. Moreover, redistribution effects are task-dependent and must be explicitly considered when assessing exoskeleton efficacy [31], [32].

At the population level, analyses with approximately twenty participants provide a reliable characterization of general exoskeleton effects without individualized personalization, aligning with prior industrial evidence [33]. However, global RMS summaries can mask adverse muscle-specific or joint-specific shifts. Bär *et al.* [34] observed increased knee joint loading with a passive back-support exoskeleton during static and dynamic tasks, indicating distal transfer of mechanical demand. Similarly, a systematic review documented altered activation patterns and localized increases in muscular effort during exoskeleton use [35]. These findings suggest that benefits at the lumbar region may coincide with increased demands on erector spinae subregions or lower-limb musculature. To mitigate such risks and improve interpretability, future studies should establish muscle- and joint–specific safety thresholds, include lower-limb joint kinetics (e.g., knee adduction and extension moments), and report distribution-sensitive outcomes in addition to global RMS.

From a methodological perspective, class imbalance was addressed using the Synthetic Minority Oversampling Technique (SMOTE), a widely adopted approach in biomedical datasets [28]. While effective for improving minority-class representation, synthetic oversampling can introduce artificial structures and amplify minority-class patterns, increasing the risk of overfitting if models are not validated on unseen participants [36]. Future work should include external validation on completely unseen participants and explore non-oversampling strategies such as cost-sensitive learning or focal loss to further enhance model robustness and generalizability.

Our sensor-driven strain detection combined with deep learning provides both statistical evidence of exoskeleton effects and a scalable framework for real-time ergonomic monitoring. Unlike traditional approaches based on peak sEMG values, subjective surveys, or task-completion metrics [25], [33], this pipeline detects both strain onset and redistribution across muscle groups through automated piecewise-regression labeling, addressing key methodological gaps in prior ergonomic research. Handling class imbalance via SMOTE and threshold tuning enabled reliable classification under data scarcity. This shift from retrospective, static analysis to continuous, adaptive monitoring aligns with recent calls for human-centered ergonomic assessment [37], [38]. The framework can be embedded in industrial cyber–physical systems to enable fatigue management, adaptive task allocation, and injury prevention. In human–robot collaboration, real-time physiological feedback could allow robots to dynamically adjust assistance levels, while managers could leverage muscle-specific redistribution insights to optimize exoskeleton deployment [39]. Beyond industrial settings, this approach also holds potential in healthcare and rehabilitation, where quantifying strain onset and redistribution could guide personalized interventions that reduce localized stress while avoiding compensatory risks, advancing next-generation occupational health systems in which ergonomic risk is continuously assessed and transparently communicated [40].

In summary, this study presents a unified sensor–AI framework that combines automated strain detection, deep learning, and muscle-specific analysis to evaluate passive exoskeletons. Results indicate reduced localized strain accompanied by compensatory load redistribution, providing a data-driven foundation for safer, more effective, and continuously adaptive ergonomic assessment.

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