Machine Learning-Based Fall Risk Detection in Human-Exoskeleton Interaction for Construction Workers

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Abstract. Physically demanding tasks in the construction industry often lead to back-related musculoskeletal disorders among workers. Active back-support exoskeletons offer a promising ergonomic solution by augmenting human strength to reduce back strain. However, their use could introduce unintended consequences such as the risk of falls. Detecting fall risks is crucial for improving workers' safety while using exoskeletons on construction sites. Foot plantar pressure provides insights into the pressure exerted beneath the feet, offering a means to evaluate stability and assess fall potential. This paper presents a machine learning framework to detect fall risk based on foot plantar pressure data collected during construction tasks involving exoskeletons, specifically carpentry framing tasks. Statistically significant differences in peak pressure between the left and right feet were used to distinguish between low and high-fall-risk scenarios during the tasks. Several classifiers including neural networks, ensemble, k-nearest neighbor, and support vector machine were employed to classify foot plantar pressure data into low and high fall risk categories. Results showed that support vector machines and ensemble methods outperformed other classifiers, achieving 63.7% accuracy with raw data and 71.9% accuracy with augmented data through jittering. This improvement highlights the effectiveness of data augmentation techniques. The study highlights the potential of machine learning techniques for real-time fall risk assessment of construction workers using active back-support exoskeletons. These findings motivate explorations of human-wearable robot interfaces to mitigate both musculoskeletal disorders and fall risks in occupational settings.

Keywords: Active back-support exoskeleton · Machine learning · Framing task · Pressure insoles · Fall risk

1 Introduction

Active back-support exoskeletons (aBSEs) have been developed to augment workers' bodies in industries where physically demanding tasks are common. According to the United States Bureau of Labor and Statistics [1], the construction industry experiences work-related musculoskeletal disorders (WMSDs) at a rate of 1.51 times higher than

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other sectors, highlighting the potential of exoskeletons as a solution. Although various studies have demonstrated reductions in muscle activations from exoskeleton use [2, 3], unintended consequences have been identified that may lead to instability of the users. These include movement restriction, uneven muscle loading, reduced cognitive capacity, and alterations in the center of gravity, all of which could reduce balance and increase fall hazards [4, 5]. Understanding the circumstances under which workers are vulnerable to falls while using exoskeletons is crucial for mitigating these risks.

Supervised machine learning has been employed to detect and classify fall risks across various fields using foot plantar pressure metrics such as center of pressure (COP) and acceleration [6, 7]. For example, Song, Ou [8] developed a machine learning model, using COP and foot acceleration, to classify different levels of fall risk for older adults. Similarly, Lee, Park [7] used COP and acceleration to develop a model for fall risk classification during different fall-related activities. Developing a supervised machine learning model requires appropriately labeled classes for training. While subjective evaluations have been used to label foot pressure data, using quantifiable metrics to determine class labels could reduce bias and subjectivity. For instance, Choi, Ralhan [9] classified participants as having low or high fall risk based on stability metrics, which were then used to train a machine learning model. Statistical differences between peak plantar pressure of the left and right foot have been indicative of instability [10].

Given the potential fall risk associated with exoskeleton use, their deployment in construction sites could exacerbate existing hazards. Despite the vulnerability of exoskeleton users, there is a lack of studies monitoring these risks during construction tasks. This study aims to explore the feasibility of detecting fall risk using machine learning algorithms based on foot data collected from users of aBSEs performing construction tasks. To address the high prevalence of back-related disorders in tasks like carpentry framing, this study uses simulated framing work as a case study to investigate these dynamics.

2 Background

While the use of exoskeletons has demonstrated some potential in reducing WMSDs, unintended consequences often occur while using the devices [11] due to mismatches in joint alignment and range of motion, which often causes instability. Over the years, studies have demonstrated how the use of exoskeletons can increase the risk of falls during various tasks [4, 12–14]. For example, Park, Kim [13] found that exoskeletons may compromise users' balance during treadmill walking. Okunola, Abiola Akanmu [4] demonstrated reduced stability when using exoskeletons for framing tasks. Schiffman, Gregorczyk [12] observed stability reductions with increasing load sizes. Gonzalez, Stegall [14] showed decreased stability while using exoskeleton on a beam. These findings collectively illustrate the stability challenges posed by exoskeletons, which could increase the risk of falls.

Deploying exoskeletons in physically demanding tasks requires monitoring the risk of fall associated with their use. Machine learning models have been developed to classify the fall risks using foot plantar pressure metrics [7, 8]. For example, Song, Ou [8] developed a machine learning model using COP and acceleration of foot plantar pressure data and achieved an accuracy of 87.5%. Lee, Park [7] developed a machine learning model using COP and acceleration of foot plantar pressure data, achieving an accuracy of 95%. While these studies demonstrate the feasibility of detecting fall risk with machine learning, training machine learning models requires that data be prepared for different classes.

Studies have adopted various methods to label data for machine learning, including subjective evaluations using scales [15] and capturing data under different conditions [16] to represent each class. However, using quantifiable metrics for data-driven decision making could help reduce bias and subjectivity [17]. For instance, Choi, Ralhan [9] used statistical significance to classify seafarers into low or high fall risk categories based on stability metrics. Statistical differences in peak plantar pressure between the left and right foot have been shown to demonstrate instability across various tasks [10, 18].

Although previous studies have explored classifying fall risks using foot data, there is limited research on detecting fall risk associated with using aBSEs during construction tasks. Given the increased fall risk associated with exoskeleton use in construction, this study aims to develop a machine learning framework to detect fall risks during framing tasks, employing an empirical, data-driven statistical approach for classifying the involved risk categories.

3 Methods

Figure 1 shows the methods adopted to achieve the objective of this study. These include the experimental design and procedure, and data collection and analysis.

Fig. 1. Methodology overview. Source: [19, 20]

3.1 Experimental Design, Instruments, and Procedure

Participants. Fourteen healthy male participants with no history of back disorders volunteered to participate in this study. The number of participants was selected based on a priori sample size computation, which provides a minimum power of 80% with an effect size (f) and alpha (α) of 0.5 and 0.05, respectively for a paired t-test. This yields a sample size of 13 participants, which is the minimum required for this study. The participants' mean age, weight, height, and body mass index are 30 ± 4 years, 72 ± 7.5 kg, 173 ± 5.5 cm, and 23.98 ± 1.9 kg/m^2, respectively. The participants provided their informed consent in accordance with the approved procedure of the Virginia Tech Institutional Review Board.

Exoskeleton. The active back-support exoskeleton, Cray X, was adopted for this study. According to the manufacturer, the exoskeleton weighs 7.5 kg and has a lifting capacity of 30 kg. It is powered by a 40-V battery that can last between 6 to 8 h. The exoskeleton is attached to the body using body straps, as shown in Fig. 2a.

Experimental Procedure. Participants recruited for the study were engaged in a simulated construction framing task that included the use of an exoskeleton (see Figs. 2b). They received orientation on the operational principles of the exoskeleton and were given time to familiarize themselves with its usage. Similarly, the sequence of the framing task was demonstrated to ensure participants' comprehension before the experiment commenced. The experiment began with the measurements of sets of timber logs required for the construction of the frame. The participants measured four pieces of 1.8 m length and two pieces of 1.2 m length, all with equal cross-sectional areas of 100 mm × 25 mm. Subsequently, they assembled the selected timber logs, followed by using a nail gun to fasten the frame together. Participants then lifted the frame and manually moved it to the next floor via the staircase for final installation.

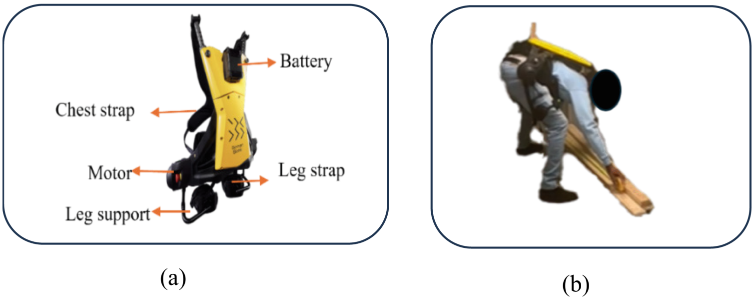


Fig. 2. (A) Active back-support exoskeleton (CrayX); (b) A participant performing the simulated framing task. Source: [19]

3.2 Data Collection

Foot plantar pressure data was captured using OpenGo wearable pressure insoles, manufactured by Moticon. The insoles are designed for both the left and right feet, each equipped with 16 sensors. The sensors are distributed across four major regions of the foot: heel, arch, metatarsal, and toe. As shown in Fig. 3, sensors 1–4 are positioned in the heel region, sensors 5–8 in the arch, sensors 9–13 in the metatarsal region, and sensors 14–16 in the toe region.

3.3 Data Analysis

The presence of artifacts in physiological data could reduce the quality of the data and subsequently affect the results. To address this issue, the foot plantar pressure data were preprocessed through a 12th-order Butterworth low-pass filter with an 8 Hz cutoff

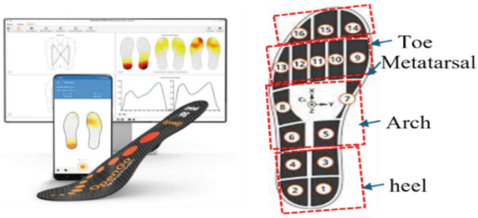


Fig. 3. Pressure insoles Source: [20].

frequency to remove artifacts [21]. Peak pressure, representing the maximum pressure exerted by each participant during the carpentry task, was computed for both the left and right feet using Eq. 1 to assess each participant's stability. The filtering process and computations were done using MATLAB 2023R and Microsoft Excel.

$$PP = Maximum\,(Pi, \ldots\ldots\ldots PN) \quad (1)$$

where Pi represents the pressure value at the i-th sensor and N represents the total number of sensors.

Statistical Analysis. To assess the stability of each participant, a paired t-test was used to evaluate the significant difference between the peak pressure of the left and right foot. Before conducting the paired t-test, the normality of the peak pressure dataset was verified using the Shapiro-Wilk test. All statistical analyses were performed using JMP Pro 17.0 and Microsoft Excel.

Data Labeling and Augmentation. Based on the outcomes of the statistical analysis, it was observed that 6 participants exhibited a low fall risk (LFR) due to their stability, while 8 participants displayed a high fall risk (HFR) due to their instability during the framing task. The classification formed the basis for the two classes examined in this study: LFR and HFR. However, there was an imbalance in the results due to the disparity in the data points between the two classes (see second column in Table 1), which could lead to bias and skew the results toward the class with more dataset. The suitability of jittering augmentation method to balance and reduce bias in data has been established by Maharana, Mondal [22]. Consequently, this method was adopted to generate augmented data aimed at balancing the LFR class, as shown in the fifth column of Table 1.

Table 1. Data labeling and augmentation.

Classes	Number of raw data points	Raw training (80%)	Raw testing (20%)	Number of augmented data points	Augmented training (80%)	Raw testing (20%)
LFR	144135	115308	28827	218100	174480	28827
HFR	218100	174480	43620	218100	174480	43620

Feature Extraction. The process of training machine learning models involves extracting important features that could impact the model's performance. The selection of features in this study was guided by the features used in previous research on fall risk and other human factors risk classification [15, 23]. Two sets of features were extracted: time and frequency domain features. The time domain features include variance, standard deviation, skewness, peak location, peak to peak, average peak, minimum, maximum, root sum of squares, median, mean, and kurtosis. The frequency domain features include median frequency, mean frequency, spectral energy, and entropy spectrum.

Classification. As shown in Table 1, the two classes of risks (i.e., LFR and HFR) were split into training and testing sets using an 80% and 20% ratio respectively. This was applied to both the raw and augmented data to prepare the data for training. The machine learning algorithms adopted for classification are Ensemble, Tree, Neural Networks, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Kernel, Binary GLM Logistics, Regression, Discriminant, and Naive Bayes, representing the top performing classifiers trained. All machine learning computations were conducted using MATLAB R2023a on a machine with an NVIDIA GeForce GTX 1060 GPU and 16GB of memory. Holdout and 5-fold cross-validation techniques were used to reduce overfitting of the machine learning models [23].

Performance Measures. Performance evaluation of the classifiers with the highest test accuracy for both the raw and augmented data was conducted using metrics such as accuracy, precision, recall, and F1 score. Accuracy measures the proportion of true results (both true positives and true negatives) among the total number of cases examined. Precision indicates the proportion of positive identifications that were actually correct. Recall refers to the proportion of actual positives that were identified correctly. F1-score combines the impact of precision and recall, providing a comprehensive performance metric. All the metrics were computed using true positive, true negative, false positive, and false negative.

4 Results

This section presents the statistical stability results and examines the extent to which fall risk levels can be detected during exoskeleton use for construction framing tasks.

4.1 Fall Risk Assessment

Figure 4 illustrates the fall risk assessment of each participant by analyzing the statistical difference between the left and right feet while performing framing tasks with the exoskeleton. The paired t-test results show that participants P4, P6, P7, P9, P10, P11, P12, and P13, demonstrate statistical significance ($P < 0.05$) between their left and right, indicating instability and thus, a high fall risk (HFR). The remaining participants do not show statistical significance ($P > 0.05$).

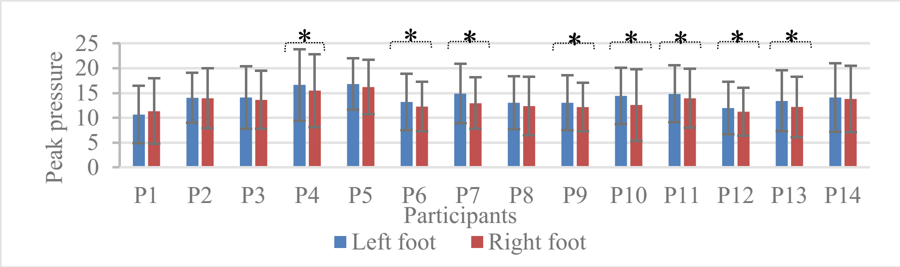


Fig. 4. Fall risk assessment ("*" = significant at p-value < 0.05).

4.2 Classifiers Performance

Figure 5 shows the test accuracy of all the trained classifier performances, with SVM representing the top-performing classifier for the raw and Ensemble for the augmented data, along with their performance.

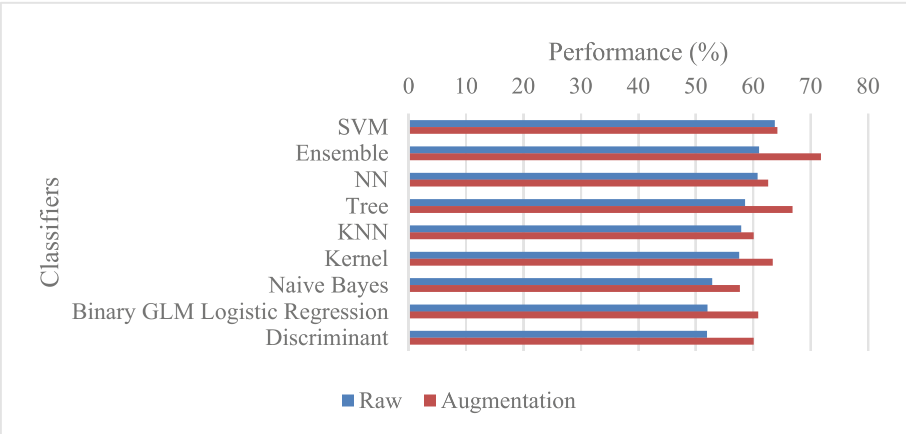


Fig. 5. Classifier performance.

Figure 6 represents the performance of the SVM classifier for the raw data and Ensemble classifier for augmented data, illustrated through precision, recall, F1-score, and test accuracy metrics. For raw data, the accuracy is 63.76%, with the HFR achieving precision, recall, and F1-score of 59.28%, 87.84%, and 70.79%, respectively. The LFR class has precision, recall, and F1-score of 76.55%, 39.68%, and 52.27%, respectively. The augmented data showed an increase in performance, with an accuracy of 71.79%. For the HFR class, the precision, recall, and F1-score are 69.63%, 77.29%, and 73.26%, respectively. The LFR class has precision, recall, and F1-score of 74.48%, 66.28%, and 70.14%, respectively.

Figures 7a and 7b illustrate the confusion matrices, showing the correct and incorrect predictions of fall risk levels for both raw and augmented data. For the raw data, the HFR

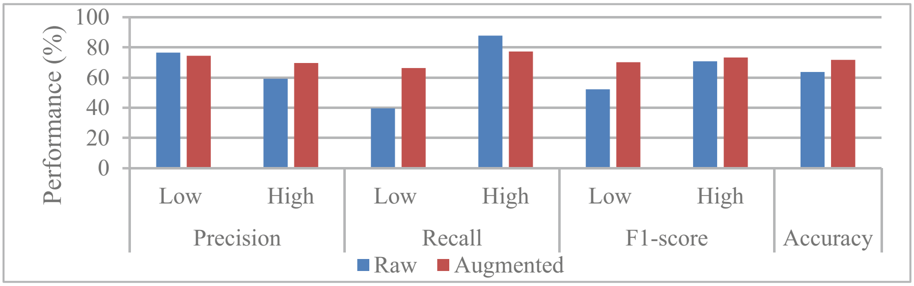
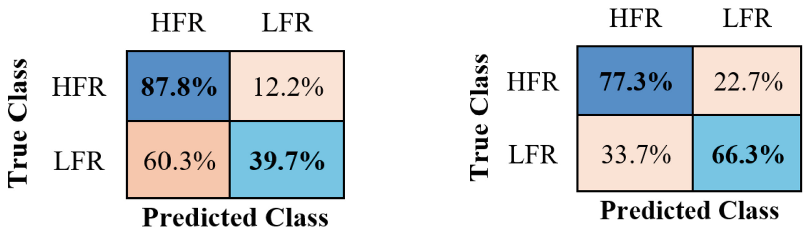


Fig. 6. Top classifier performance.

class is predicted correctly 87.8% of the time, while the LFR class is predicted correctly 39.7% of the time. In contrast, with the augmented data, the HFR class is predicted correctly 77.3% of the time, and the LFR class is predicted correctly 66.3% of the time.



(a) (b)

Fig. 7. Confusion matrix: (a) raw data; (b) augmented data.

5 Discussion

The results of this study have significant implications for the use of aBSEs on construction sites, particularly concerning the risk of falls. The statistical analysis reveals that a substantial number of participants exhibited significant instability while using aBSEs, as indicated by the differences between the left and right foot plantar pressures. This could be due to misalignment between the exoskeleton's support and the natural movement of the human body, corroborating previous findings that exoskeleton use can compromise balance [12, 13]. The remaining participants did not show significant differences, indicating that the risk of falls may vary widely among users. The inconsistency in stability highlights the need for personalized fitting and adjustments to ensure the exoskeleton's alignment with the user's body mechanics [14].

The performance of the Ensemble classifier, especially with augmented data, demonstrates that machine learning models can effectively classify fall risk levels with reasonable accuracy, although misclassification rates indicate there is still room for improvement. The effect of class imbalance is evident in the high variance of misclassification rates between the two classes, with the underrepresented LFR class experiencing a higher misclassification rate, which was mitigated after augmentation. These mis-classification rates underscore the limitations of the current models in accurately predicting and classifying fall risk levels. This issue may stem from the challenges the machine learning algorithm faces when handling complex data from pressure insoles. The observed misclassifications highlight the need for more robust predictive learning models capable of consistently and accurately assessing fall risk across different conditions and user behaviors. The implications of the findings for the construction industry are critical, as the demonstrated instability suggests that while aBSEs have the potential to reduce WMSDs, they may inadvertently increase the risk of falls if not properly fitted or if the user's movement patterns are not adequately supported. To mitigate these risks, construction companies could ensure individualized fitting and adjustment of exoskeletons [2], provide comprehensive training programs [11], integrate real-time monitoring using machine learning models [23], and implement regular assessment and feedback loops.

6 Conclusions, Limitations, and Future Work

This study investigates the extent to which the fall risk of exoskeleton users can be recognized using foot pressure data while performing framing tasks. Stability assessments of the left and right feet of participants were used to label foot pressure data for machine learning. The SVM and Ensemble classifiers performed best with raw and augmented data, respectively, with an improvement noted after data augmentation, demonstrating the feasibility of predicting fall risk from foot pressure data.

However, the use of a specific exoskeleton model in this study may limit the generalizability of the findings to other models. Future research should investigate different exoskeleton models. Additionally, since the study was conducted with students in a laboratory setting, it may not fully replicate real construction site conditions, such as uneven surfaces that could exacerbate exoskeleton instability. This limitation may affect the reliability and validity of the results compared to those from experienced construction workers on actual sites. Future work should include experiments with experienced workers in real construction environments and explore various exoskeleton models to enhance the applicability of the findings. This study paves the way for developing AI-based systems to monitor and mitigate fall risks associated with exoskeleton use in construction environments.

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