Machine learning-based identification and classification of physical fatigue levels: A novel method based on a wearable insole device

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Highlights

- Physical fatigue levels in construction were identified and classified.
- Acceleration and plantar pressure data were collected from wearable insole device.
- The performance of five supervised machine learning classifiers was assessed.
- Random Forest classifier achieved the best performance with an accuracy of 86%.
- This study contributes to mitigating fatigued-related injuries in construction.

Abstract
Construction is known for being a labor-intensive and risky industry. Within various occupational settings such as construction, physical fatigue is an underlying health condition that may lead to musculoskeletal disorders and fall-related injuries. Identifying a worker's physical fatigue could enable safety managers to mitigate fatigue-related injuries and improve workplace operations. However, current physical fatigue assessment and identification methods include subjective, physiological, biomechanical, and computer vision approaches, which may be unreliable, intrusive, and require extensive post-processing, thus, rendering them impractical for continuous monitoring of workers' movements and automated identification of physical fatigue. Given the above, this study aims to utilize a wearable insole device to identify and classify physical fatigue levels in construction workers. Ten asymptomatic subjects were recruited to perform a fatiguing manual rebar tying activity in a laboratory setting. Borg's rating of perceived exertion (RPE) was applied as a subjective measure for collecting the levels of physical fatigue of each subject. Three sub-classification problems for identifying physical fatigue levels (i.e., PFL1, PFL2, and PFL3) were assessed. Numerous features were evaluated from the collected data samples after data segmentation. The classification performance of supervised machine learning algorithms was evaluated at a sliding window of 2.56 s. Our results from 10-fold cross-validation show an accuracy of 86% for the Random Forest (RF) algorithm, indicating the best performance among other algorithms. In addition, precision, recall, specificity, and F1-score metrics of the RF algorithm were between 52.63% to 82.62%, 52.63% to 84.32%, 89.60% to 92.33%, and 52.63% to 83.46%, respectively. These results indicate that data samples such as acceleration and plantar pressure acquired from a wearable insole device are reliable for identifying and classifying physical fatigue levels in construction workers. In summary, this study would contribute to providing a proactive physical fatigue assessment method and guidelines for early identification of physical fatigue in construction.

Keywords: Fatigued-related injuries; Machine learning; Musculoskeletal disorders; Physical fatigue; Wearable sensors.

1. Introduction

With various occupational injuries, the construction sector is a complex and risky environment in the world [1]. This could be attributed to the fact that it is a labor-intensive industry with physically demanding workplace activities, which are directly associated with occupational injuries. It was reported by the Bureau of Labor Statistics (BLS) that the US construction industry registered about 970 and 200,000 incidents related to fatal and non-fatal events, respectively in 2017 [2]. The Australian construction industry was also responsible for 36 out of 194 fatalities in 2020, resulting in a 3.1 fatality rate throughout every industry [3]. Despite significant research efforts on implementing effective preventive measures to mitigate occupational injuries, the rate of injuries within the construction industry is still high.

Construction workplace activities are usually dynamic, physically demanding, and repetitive. These activities are performed manually over a long period, in a hostile atmosphere, and without enough recovery [4]. Accordingly, construction workers are likely to experience physical fatigue, which can also lead to musculoskeletal disorders as well as other fall-related incidents. It has been reported by the Occupational Safety and Health Administration (OSHA) that physical fatigue is among the four major causes of fatal instances in construction (40% of fatalities in 2014) [5]. The adverse effects of physical fatigue might lead to workers being away from work, high cost of medical premiums, and lack of productive working periods [6, 7]. Since physical fatigue can pose severe health-related issues to construction workers, identifying workers' physical fatigue levels is undoubtedly worth studying. More specifically, it is essential to identify workers' physical fatigue levels to ultimately prevent fatigue-related injuries and improve their productivity [8].

1.1. Physical fatigue measurement methods

Besides construction, there are a variety of ways for assessing physical fatigue in other occupations. Several decades ago, the assessment of physical fatigue in different occupational settings was conducted through self-reported methods [8—10]. Self-reported methods for assessing physical fatigue enabled workers to rate their level of perceived exertion by using questionnaires, and rating scales [11, 12]. The Borg's Rating of Perceived Exertion (RPE) [13], Need for Recovery Scale (NRS) [14], and Fatigue Assessment Scale (FAS) [15] are examples of self-reported methods. Although they are simple and straightforward, self-reported methods are limited to assessing workers' physical fatigue because: (1) they depend on workers' subjective perceptions and thereby may lead to biased results; (2) they are incapable of showing changes in fatigue over time during ongoing activity, making them impractical for continuous monitoring of workers' physical fatigue; (3) data collection is usually time-consuming, cumbersome, and the procedure can interfere with workplace activities [7].

Another way to quantify workers' physical fatigue is to use biomechanical models, which examine human motions and determine joint loadings [16]. Extant research studies have indicated that electromyography-assisted biomechanical models and remote-sensing techniques may be used to evaluate workers' movements and internal joint loadings [16—18]. A study by Seo et al. [16] presents a simulation-based framework based on biomechanical analyses to estimate physical demands and fatigue during construction operations. Biomechanical models have great prospects for analyzing motion data captured by remote sensing techniques to evaluate physical fatigue of workers. However, huge amount of datasets are required, and errors occur because of the configuration of the biomechanical skeleton models of the joint locations [19]. Moreover, data collection is usually conducted in a laboratory setting by attaching markers to participants, which makes their application on construction sites very unsuitable.

The most widely used methods for monitoring and assessing physical fatigue are by employing physiological methods. Examples include heart rate (HR), electrodermal activity (EDA), skin temperature (ST), heart rate variability (HRV), surface electromyography (sEMG), and electroencephalography (EEG) [20—26]. These physiological methods usually employ different wearable sensors (e.g., headsets, chest straps, and wristbands). During a simulated repetitive lifting job, Antwi-Afari et al. [22] applied sEMG signals to measure muscle activity and fatigue. Chang et al. [20] conducted a study on physiological symptoms and fatigue experienced by high-elevation construction workers, finding HR as a useful fatigue assessment in construction. Based on other physiological measurements (e.g., photoplethysmogram (PPG), EDA, and ST), Jebelli et al. [24] validated a non-invasive technique for monitoring and identifying employees' physical demand levels. Although they are all useful for monitoring and assessing workers' physical fatigue [23, 27, 28], there are few challenges to physiological signals. First, sEMG requires electrodes to be directly attached to workers' skin surfaces to measure physical fatigue. These electrodes record the electrical activity of human movements, but they can easily cause body irritation since electrodes are highly invasive and the electrical signals are susceptible to extreme environmental conditions. Second, measuring physiological methods such as EEG is not an easy process because of intrinsic artefacts like facial attributes on muscle groups [25, 29]. Third, physiological approaches like HR, EDA, and ST that are measured by using a wristband-type biosensor in real-world settings may lead to extrinsic signal artifacts, environmental noises, and sensor displacement [30, 31]. Given the above, an objective, continuous, and non-invasive approach is still needed to identify and classify physical fatigue levels in construction.

Computer vision-based methods provide a non-invasive approach to observe human movements and assess physical fatigue during indoor or outdoor environments [32—34]. Using high-resolution human motion capture to characterize external load conditions when walking, Lee et al. [35] suggested a linear discriminant analysis approach. Similarly, using vision-based 3D motion capture (i.e., RGB camera), Yu et al. [33] investigated a non-invasive method to predict physical fatigue of construction workers. Their proposed method could automatically calculate joint-level physical fatigue assessment. Although computer vision-based methods are highly accurate, they have some drawbacks including: (1) they cannot be used for continuous monitoring outside laboratory environments; (2) they are occasionally ineffective with moving backgrounds and have privacy issues; (3) they are highly costly and require a large installation space and lighting conditions [36, 37].

In recent years, wearable inertial measurement units (WIMUs) systems have been widely employed to monitor human body reactions or gait patterns during simulated work activities [38—40]. Existing literature had used WIMUs-based systems to distinguish between physically fatigued and normal gait (i.e., non-fatigued) states based on human movement patterns [41—43]. Baghdadi et al. [43] detected fatigue states following manual material handling by using a single WMIU on the subjects' ankle. Zhang et al. [41] explored the classification potential between normal and fatigued states by collecting kinematic and kinetic gait patterns from a WIMU. Maman et al. [42] utilized a novel method to assess physical fatigue in simulated manufacturing tasks by using WIMU and a HR monitor. Taken together, these studies reported changes in either gait parameters or kinematic features captured by using WIMUs in occupational settings, providing a foundation for monitoring human movements and physical fatigue identification. However, the experimental procedures do not mimic typical real-world construction tasks. In addition, most of these previous studies classified physical fatigue from a binary classification perspective such as fatigued and non-fatigued states, thus, providing insufficient knowledge for safety managers for identifying workers' physical fatigue levels. In the construction realm, workers' physical fatigue has been monitored and assessed based on real-time motion data collected using WIMUs-based systems [44, 45]. Even though they are useful, WIMUs-based systems not only cause body discomfort due to attaching sensors to workers' bodies but also add attachments such as straps and belts that can interfere with work performance.

Given the aforementioned constraints, this current study suggests a wearable insole device as a noninvasive approach for automatic identification and classification of workers' physical fatigue levels. The suggested device may be readily inserted and removed from workers' safety shoes, reducing human body restrictions [46]. Compared to other traditional methodologies, the proposed device is simple, convenient, and enables an objective data collection process during a dynamic working environment. Moreover, a wearable insole device is not susceptible enough to interfere with ongoing workplace activities. Overall, it has great potential to assess and monitor workers' physical fatigue levels in a laboratory or real construction setting.

1.2. Machine learning-based wearable sensing data for identifying physical fatigue

Recent growing interests in combining machine learning algorithms and wearable sensor data had been demonstrated for automated identification and classification of physical fatigue. Numerous previous studies have focused on identifying workers' physical fatigue based on machine learning algorithms and physiological data such as EEG, EDA, ST, and PPG [23, 24, 26, 28, 31, 47]. By performing a construction task (i.e., manual material handling), Aryal et al. [23] trained the Boosted tree algorithm on features extracted from HR, ST, and EEG sensors. Their results achieved an accuracy of 82% for predicting physical fatigue levels. By adopting machine learning-based physiological measurements like photoplethysmogram (PPG), EDA, and ST, Jebelli et al. [24] validated a non-invasive method to assess workers' stress levels. Umer et al. [28] investigated the utilization of integrated cardiorespiratory and thermoregulatory measurements and machine learning algorithms to predict physical exertion. Their proposed approach could predict exertion levels with a high accuracy of 95.3%. Similarly, Umer et al. [26] recently studied how HRV features could be utilized to model physical exertion based on different types of machine learning algorithms. Ensemble algorithms were shown to have accuracies ranging from 64.2% to 81.2%. Overall, previous studies have contributed to improving workers' productivity and safety by providing objective and reliable early detection of physical fatigue based on different types of physiological sensing data collected during laboratory or construction workplace settings. However, physiological sensing signals are not sufficient to continuously monitor workers' physical fatigue with a variety of demographic traits while executing workplace activities with insufficient time [24].

Other researchers have also demonstrated novel approaches to detect workers' physical fatigue based on machine learning algorithms and gait patterns or bodily motion data captured from WIMUs-based systems [42, 43, 45, 48]. Baghdadi et al. [43] examined a single WIMU for continuous monitoring of physical fatigue. The support vector machine algorithm (SVM) was adopted to classify non-fatigued and fatigued states. Yang et al. [48] explored a novel method with WMIU embedded in a smartphone and SVM for evaluating workers' labor intensity. Fardhosseine et al. [45] developed a framework to detect workers' physical fatigue by evaluating the changes in gait patterns measured by WIMU embedded in a smartphone. These authors achieved accuracies of 87.93% and 82.75% using linear and non-linear SVM, respectively. Combined, existing studies reveal the viability of using WIMUs to achieve high accuracies of physical fatigue monitoring and workers' physical demands in both laboratory and real-world settings. However, as previously stated, it necessitates the attachment of sensors to the participants' bodies, thus, causing distress.

1.3. Research gap and objective

Previous studies have assessed workers' physical fatigue by using various traditional methods like self-reports. These physical fatigue assessment methods are basically subjective and time-consuming [12—15]. Since subjective assessment of workers' fatigue levels is based on their individual differences in intuitions or experiences, they are relatively biased. To address these limitations in traditional methods, numerous studies have utilized biomechanical analyses and electrophysiological measurements like EEG, HR, HRV, ST, sEMG, and EDA [22, 26—29, 49]. On one hand, biomechanical analysis methods for assessing workers' physical fatigue mainly use force plates, WIMUs, or computer vision-based systems [32, 33, 41, 45]. Few limitations to using these methods include: (1) force plates cannot continuously monitor workers' physical fatigue outside laboratory environments [41]; (2) WIMUs are generally intrusive and can lead to workers' discomfort; and (3) computer vision-based systems may provide inaccurate results due to the influence of sunlight during data collection. Wearable biosensors, on the other hand, are primarily used to capture electrophysiological signals. Even though these sensors are beneficial and provide good accuracy for physical fatigue monitoring, attaching them to various body regions may cause irritation, restricting their use in real-world construction environments [44]. Consequently, a noninvasive measurement method is needed to continuously monitor and identify physical fatigue based on a simulated construction setting.

Therefore, this study aims to utilize a wearable insole device for automated identification and classification of physical fatigue levels in construction. To achieve the stated aim, we collected plantar pressure and acceleration data from a wearable insole device during a fatiguing manual rebar tying activity conducted in a laboratory setting. Notably, Borg's rating of perceived exertion (RPE) was used as a subjective scale to measure the level of physical fatigue exposed to the subjects. Relevant features were extracted after dividing collected sensor streams into a smaller window segments. To categorize workers' physical fatigue levels, supervised machine learning algorithms were used. In summary, this study would enhance real-time detection of physical fatigue in construction workers, thus, improving their safety and productivity.

2. Research methods

To achieve the stated research objective, we recruited ten healthy male subjects to conduct a simulated fatiguing manual rebar tying activity. A wearable insole device was inserted into subjects' safety shoes to collect acceleration and plantar pressure data. Pre-processing of the collected data was performed, and the processed data were further divided into smaller data segments by adopting the sliding window technique. Three types of features: (1) time-domain, (2) frequency-domain, and (3) spatio-temporal features were examined and used as input vectors for algorithm training and validation. Subsequently, the extracted features were manually labelled using the subjects' Borg RPE scores. Considering five kinds of supervised machine learning algorithms: (1) Support Vector Machine (SVM), (2) Artificial Neural Network (ANN), (3) K-

Nearest Neighbor (KNN), (4) Random Forest (RF), and (5) Decision Tree (DT), we trained the extracted feature vectors to evaluate the feasibility of identifying and classifying workers' physical fatigue levels. Figure 1 depicts the research framework.

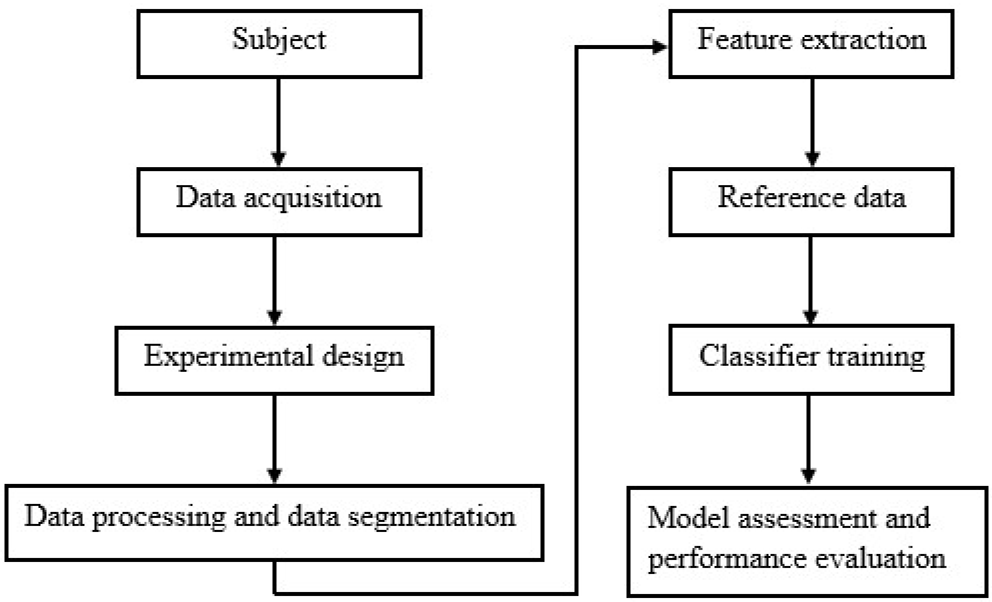

Fig. 1. Research framework

2.1. Subjects

Ten healthy male student subjects volunteered to participate in this experiment. The mean ± SD age, weight, height, and shoe size were 32.4 ± 3.17 years, 76.2 ± 8.63 kg, 1.72 ± 0.11 m, and 40.50 ± 0.79 European, respectively. All subjects had basic construction experience of performing a manual rebar tying activity, which was the physically fatiguing task performed during laboratory experiments. The subjects had no history of (1) low back disorders, (2) neurological disorders, or other health issues that would have prevented them from completing the experiment. These exclusion criteria were enforced by ensuring that they were capable of and comfortable participating in the experimental trials. Before the experimental trials, all subjects were fully informed of the detailed experimental protocol, and they provided their informed consents.

2.2. Data Acquisition

To capture acceleration and plantar pressure data, the current study utilized an OpenGo wearable insole device (Moticon SCIENCE Sensor Insole GmbH, Munich, Germany) for data collection.

Table 1 shows the detailed specifications of the proposed wearable insole device. The sampling frequency used for the collected signals was 50 Hz. Figure 2 shows an overview of the wearable insole device and user interface. The sensor insoles were inserted into a pair of safety shoes for collecting plantar pressure distribution and acceleration data. Previous studies have shown that the wearable insole device is a reliable and accurate sensing system for activity recognition and work-related risk factors identification [46, 50, 51].

The current study used Borg's RPE [13] to record the subjects' perceived level of physical fatigue in every 2 mins during data collection. Borg's RPE is a basic and subjective rating scale that ranges from 6 to 20 with information ranging from "No physical exertion at all" to "Maximal exertion." The Borg-20 scale is an authentic measure for evaluating physical demands/exertions during manual material handling activities in earlier studies, with subjects' maximum physical exhaustion occurring when RPE was equal to or more than 17 [23, 42, 47, 52].

Table 1. Specifications of a wearable insole device

Parameter	Description
Pressure sensor	
Size	40/42 EU
Quantity	16 per insole sensor
Range of pressure	0.0 to 50.0 N/cm^2
Resolution	0.25 N/cm^2
Hysteresis	≤ 1%
Wireless transmission	Bluetooth low energy 5.0
Wireless range	≥ 5.0 m
Bandwidth	54 kB/s
Principle	Force capacitive pressure sensors
Power supply	With rechargeable coin cells (PD2032)
On-board memory storage	16 MB
Accelerometer	
Principle	Inertial mass
Quantity	1 per insole sensor
Type	3-axis gyroscope and a 3-axis accelerometer
Acceleration range	± 16g
Angular rate range	± 2000 dps
Position	Midfoot with respect to gravity
Coin cell rechargeable	3.7 V ± 0.4V

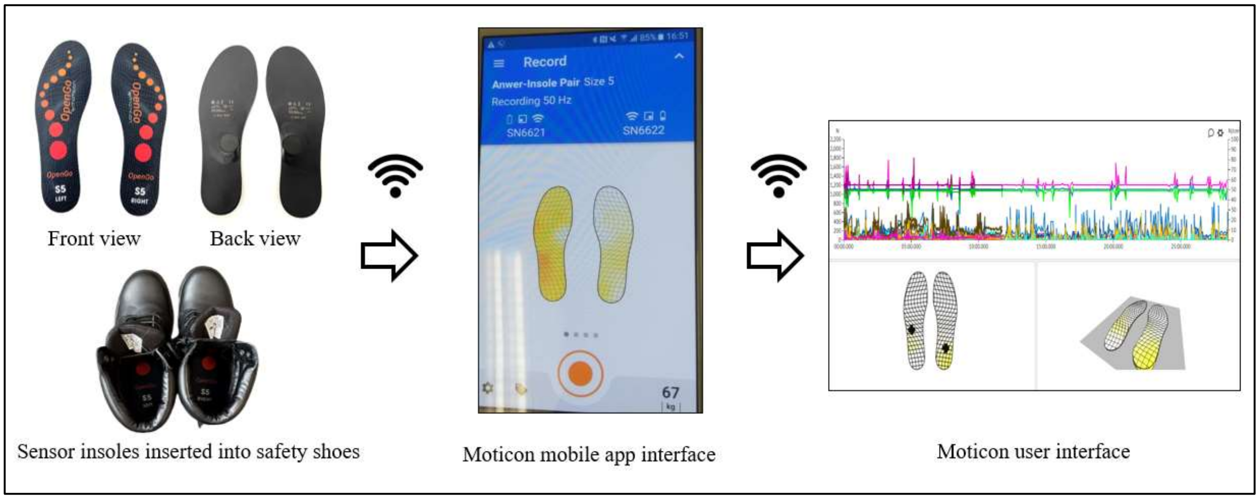

Fig. 2. An overview of the wearable insole device and user interface

2.3. Experimental Design

This study used a single-visit cross-sectional study design. The experiments were simulated in a laboratory setting where the subjects conducted a physically fatiguing task involving a manual rebar tying activity, particularly common among construction rebar workers. A manual rebar tying activity was chosen because it has been exhibited to cause different perceived exertion levels, including whole-body physical fatigue and postural instability [53, 54]. Existing studies have also shown that a high prevalence of musculoskeletal disorders (e.g., low back pain) and physical fatigue in rebar workers are attributed to performing repetitive rebar tasks in prolonged awkward working postures [55, 56].

Upon arrival at the laboratory, the experimental design was described to the subjects before starting the actual data collection. Next, they gave their individual informed consent and demographic status. To simulate a real-world physically fatiguing task in construction, each subject was asked to practice the manual rebar tying activity for 5-min each. The training session also served as a warm-up for the physically fatiguing tasks. During the training session, all the subjects wore safety shoes with an inserted wearable insole device, a reflective safety vest, and a safety helmet. After training sessions, the subjects were asked to rest before performing the actual experiments for data analyses. The resting period intends to avoid any fatigue effects before starting the experiments. To decrease the influence of pressure due to tightening of the safety shoes, all plantar pressure sensors were zeroed before the actual data collection began.

During data collection, the subjects were asked to walk comfortably on a path of approximately 5 m to collect their baseline data (i.e., normal walking). The walking path was properly marked on the floor to guide the subjects during data collection. After completing baseline data, each subject performed a physically fatiguing task involving a manual rebar tying activity. The simulated manual rebar tying activity was a setup made of top and bottom reinforcement bars arranged in a wooden formwork like a slab rebar construction formwork in a real-world construction site. The subjects were instructed to use a plier and steel wires to tie the top and bottom joints of rebars. Figure 3 presents the simulated manual rebar tying setup. During the manual rebar tying activity, the subjects were not allowed to change postures to keep consistency and standardization within the entire experimental protocol. For every 2 mins, the subjects were asked to provide their verbal subjective physical exertion using the Borg RPE scale. Immediately after being given their Borg's RPE, they were instructed to walk on the marked path to collect their fatiguing data. The process of conducting the simulated manual rebar tying activity, providing Borg's RPE every 2 mins, and collecting fatiguing data while walking continued until the subjects' Borg's RPE reached a score ≥ 17, indicating a maximal exertion in agreement with Borg's RPE. Overall, the start and end of each subject's experimental trial were determined as the instant of collecting baseline data (i.e., normal walking) and subjectively recording their physical fatigue on Borg's RPE score ≥ 17, respectively. In summary, four physical fatigue levels are tested based on subjects' Borg's RPE score during manual rebar tying activity. The examined physical fatigue levels are baseline or no-level physical fatigue (Borg's RPE score of 6), low-level physical fatigue (Borg's RPE score of 7-11), medium-level physical fatigue (Borg's RPE score of 12-16), and high-level physical fatigue (Borg's RPE score of ≥ 17), which were labeled in this present study as NLPF, LLPF, MLPF, and HLPF, respectively. Figure 4 shows samples of plantar pressure distribution and acceleration signals for each level of physical fatigue. As shown in Figure 4, the collected signals were distinct from each other. Therefore, we examined three sub-classification problems to assess the classification performance of identifying physical fatigue levels using a wearable insole device during a manual rebar tying activity: (1) PFL1: identifying the existence of physical fatigue levels (NLPF vs LLPF, MLPF, HLPF); (2) PFL2: identifying the no-level, low-level, and high-level physical fatigue levels (NLPF vs LLPF vs HLPF); and (3) PFL3: identifying all physical fatigue levels (NLPF vs LLPF vs MLPF vs HLPF). The entire experimental trials of each subject performing a manual rebar tying activity were recorded synchronized using a video camcorder.

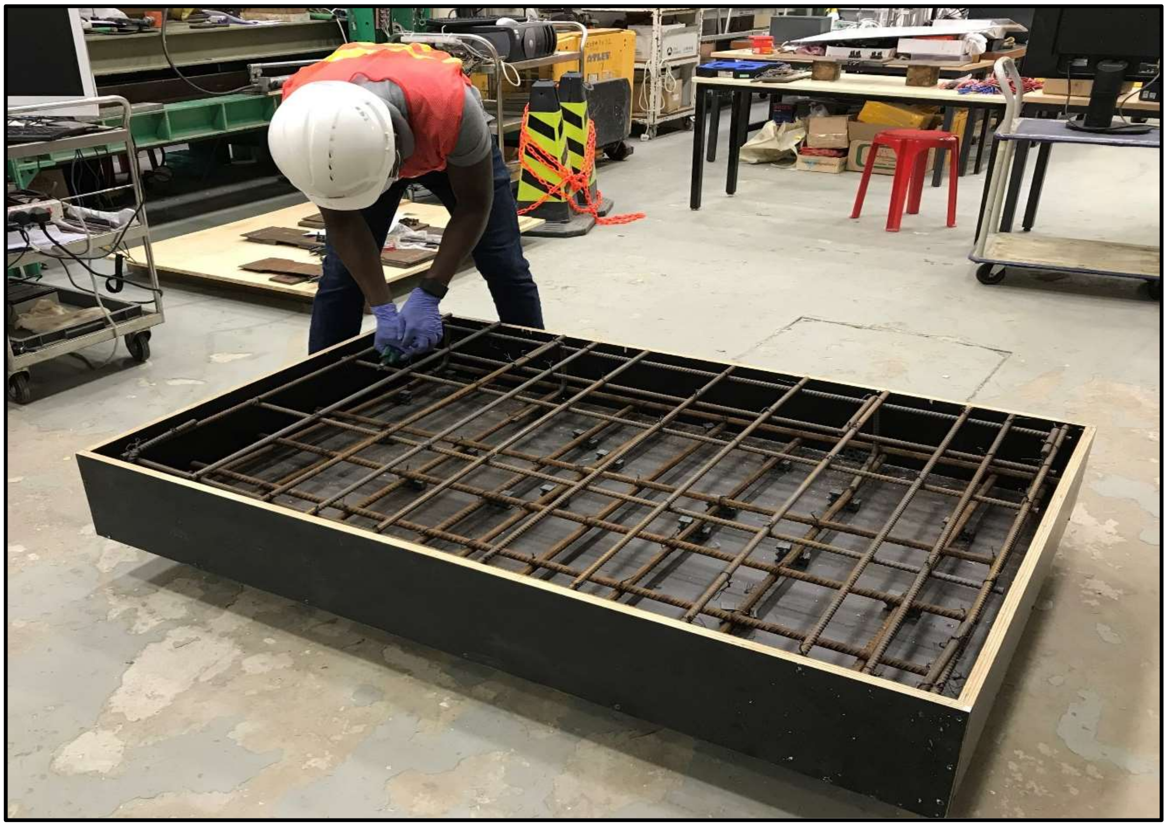

Fig. 3. A simulated manual rebar tying activity

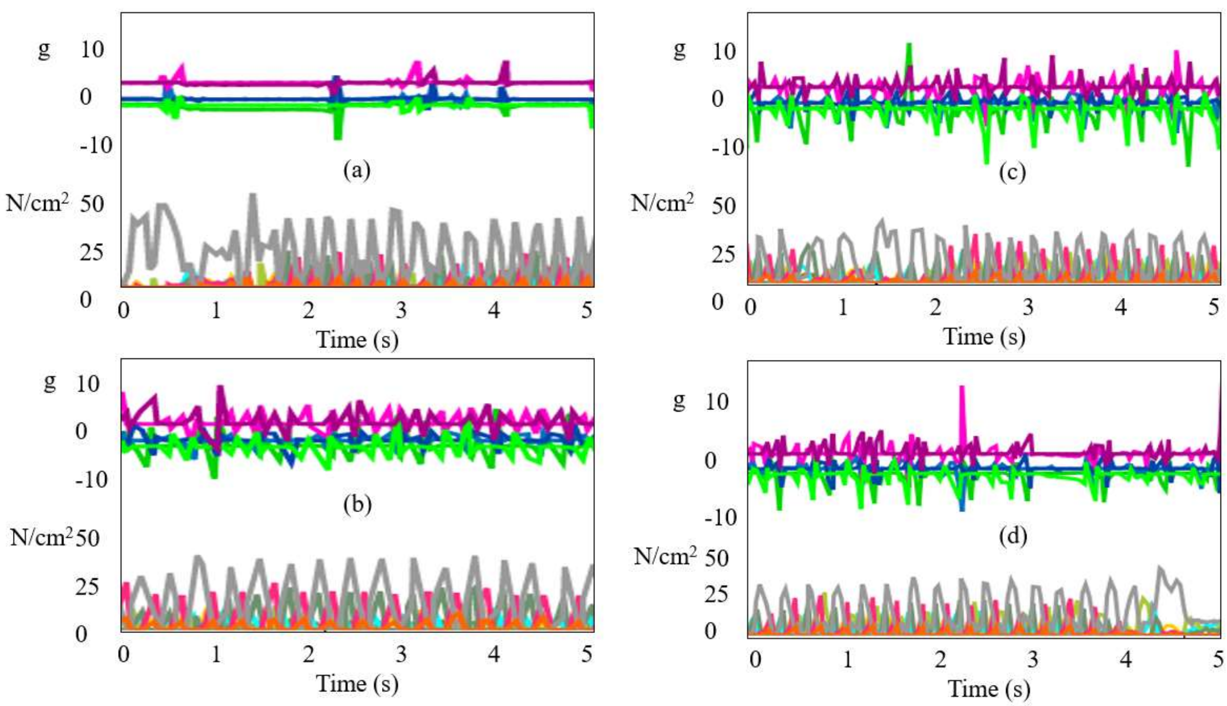

Fig. 4. Collected samples of plantar pressure distribution and acceleration signals for each level of physical fatigue: (a) baseline or no-level physical fatigue (NLPF); (b) low-level physical fatigue (LLPF); (c) medium-level physical fatigue (MLPF); and (d) high-level physical fatigue (HLPF)

2.4. Data processing and data segmentation

Data processing and segmentation was the next step to laboratory data collection. Initially, the acquired raw data was saved on each insole sensor's inbuilt memory storage. After that, all of the information were wirelessly uploaded to a desktop computer and converted to an excel file. Only plantar pressure patterns and acceleration signals were analyzed in this investigation and used in subsequent analyses. As such, they consist of 16 plantar pressure data and 3-axis acceleration signals separated for the left and right sensor insole. Taken together, a total of 38 dependent variables, consisting of thirty-two plantar pressure patterns, and six acceleration signals were considered for data processing and further analyses. To reduce the effects of body segment movements, the plantar pressure patterns were low-pass filtered using a second-order Butterworth filter with a 1 Hz cut-off frequency [57]. In addition, acceleration signals were filtered using a second-order Butterworth low-pass filter with a 4 Hz cut-off frequency. The purpose of data filtration was to remove sensor noise or signal artefacts and any disrupted signals during walking after performing fatiguing manual rebar tying activity. Consequently, the processed data enable relevant data samples to be preserved before data segmentation, and previous studies have adopted similar data filtering [58, 59].

After data filtering, the pre-processed data were further divided into smaller data segments using the sliding window technique [45]. A window segment of 2.56 s was used in this study. Since we had to convert time-domain to frequency-domain using fast Fourier transforms (FFT) in MATLAB 9.2 software (Matlab, The MathWorks Inc., MA, USA) with the window segment to be a power of 2, this window segment was chosen [46, 50]. In addition, a larger range of window segments (i.e., 0.08 to 10.24 s with an increment of power of 2) was tested in a pilot study to find the optimal window segment. By considering the conducting experiments, a window segment of 2.56 s, which corresponds to 128 (2^7) data samples were selected as the optimal window segment because it obtained the highest overall classification performance. A 50% overlap of the adjoining window was used in this research to reduce redundant data samples [46, 51].

2.5. Feature Extraction

After data processing and data segmentation, relevant features were extracted to serve as input variables for identifying physical fatigue levels. A total of 38 dependent variables were converted into representative feature values. Previous studies have commonly used several feature types like (1) time-domain, (2) frequency-domain, and (3) spatio-temporal features in activity recognition and detection [46, 50, 60]. In this study, representative features that had already shown significant distinctive results in workers' activity and work-related risk factor identification based on plantar pressure data and acceleration signals were selected [46, 51]. Table 2 illustrates a summary of the extracted feature types. As indicated in Table 2, the extracted feature types consist of twelve time-domain features, two frequency-domain features from the fast Fourier transform (FFT) analysis, and three spatio-temporal features from only plantar pressure data. Then, all extracted feature values were labelled with the subjective RPE scores of the subjects so that they could be used for algorithm learning and classification performance.

Table 2. Summary of extracted feature types

Feature type	Name	Expression
Time-domain	Mean	$\frac{1}{N}\sum_{i=1}^{N} Wi$
	Variance	$\frac{\sum_{i=1}^{N}(W_i-\mu)^2}{N}$
	Maximum	Max $(Wi, \ldots, W_N)$
	Minimum	Min $(Wi, \ldots, W_N)$
	Interquartile range (IQR)	$Q_3 - Q_1$
	Standard deviation	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(W_i-\mu)^2}$
	Root mean square (RMS)	$\frac{1}{N}\sum_{i=1}^{N} {W_i}^2$
	Kurtosis	$\frac{1}{N}\sum_{i=1}^{N}\left(\frac{W_i-\mu}{\sigma}\right)^4$
	Skewness	$\frac{3(\mu-\tau)}{\sigma}$
	Standard deviation magnitude	$\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(W_i-\mu)^2}$
	Sum vector magnitude	$\frac{\sum_{i=1}^{N}\sqrt{x_i^2+y_i^2+z_i^2}}{N}$

	Signal magnitude area	$\frac{\sum_{i=1}^{N}(\lvert x_i\rvert + \lvert y_i\rvert + \lvert z_i\rvert)}{N}$
Frequency-domain	Spectral energy	$\sum_{i=1}^{N} \lvert p(N)\rvert^2$
	Entropy spectrum	$-\sum_{l=1}^{N} P(l)\log(P(l))$
Spatiotemporal	Pressure-time integral	$\sum_{t=1}^{N} P_i \times \Delta t$
	Anterior/Posterior centre of pressure	$\frac{\sum_{i=1}^{N} XiPi}{\sum_{i=1}^{N} Pi}$
	Medial/Lateral centre of pressure	$\frac{\sum_{i=1}^{N} YiPi}{\sum_{i=1}^{N} Pi}$

Note: W_i = the *i*th acceleration or pressure sensor; N = the total number of acceleration or pressure sensor data; Q_i = the ith quartile; μ = mean; σ = standard deviation; τ = median; x_i= the ith acceleration of the x-axis; y_i = the ith acceleration of the y-axis; z_i= the ith acceleration of the z-axis; *P(l)* = power spectral density; Δt = the time interval; P_i = the *i*th pressure sensor; X_i and Y_i = the coordinate values for *i*th pressure sensor.

2.6. Reference Data

The physical fatigue levels corresponding to the collected data were annotated by physically observing the recorded video and Borg's RPE. The goal of reference data in human activity recognition related research work is to establish a baseline against which models may be evaluated [46, 60]. In this study, there are 4 main classes of physical fatigue levels. As such, no-level physical fatigue, low-level physical fatigue, medium-level physical fatigue, and high-level physical fatigue were manually labelled as classes 1, 2, 3, and 4, respectively.

2.7. Classifier Training

Extracted features with labelled classes were trained on five kinds of supervised machine-learning algorithms, namely: (1) ANN, (2) DT, (3) RF, (4) KNN, and (5) SVM. These machine learning algorithms were selected because they are commonly adopted for human activity recognition studies based on wearable sensor data such as acceleration, pressure, etc. [46, 50, 60]. A multilayer feed-forward neural network, also known as a multilayer perceptron (MLP), was employed for ANN [61]. The Levenberg-Marquardt method with a sigmoid transfer function was chosen to minimize the cost function throughout the training procedure [62]. Meanwhile, the classification and regression tree (CART) and Gini diversity index were used for training DT algorithm [60]. In training a RF algorithm, two model parameters such as mTry and nTree were set at 6 and 500, respectively [63]. For KNN algorithm, the Euclidean distance was selected in this research [60]. A multi-class one-against-one approach was employed to train the SVM algorithm with the Gaussian radial basis function (RBF) used for mapping the inputs to a high dimensional space [60, 64]. The 'Classification Learner' App in MATLAB was not only utilized to train machine learning algorithms but also for evaluating classifier model assessment and performance.

2.8. Model Assessment and performance evaluation

For model assessment, *k*-fold cross-validation was applied. In this method, the original training set is randomly divided into *k* sub-dataset. *K*–1 sub-dataset is applied to train models and a remaining sub-dataset is used to validate models. Since *K* was set as 10 in this study, the dataset is randomly split into 10 approximately equal-sized exclusive subsets. Then, each sample has an opportunity to train and validate models with a particular algorithm [65]. For performance evaluation, the accuracy, precision, recall, specificity, and F1 score were adopted to evaluate the best algorithm [66]. In addition, the performance of the best algorithm for three sub-classification problems, including (1) PFL1 – (NLPF vs LLPF, MLPF, HLPH); (2) PFL2 – (NLPF vs LLPF vs HLPF); and (3) PFL3 – (NLPF vs LLPF vs MLPF vs HLPF) was assessed using a confusion matrix. Equations 1 to 5 show how each metric is calculated. TP is True Positive; TN is True Negative; FP is False Positive; and FN is False Negative.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$Specificity = \frac{TN}{TN + FP} \quad (4)$$

$$F - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

3. Results and Discussion

The present study aimed to develop a novel method for identifying and classifying physical fatigue levels by combining wearable insole data and machine learning algorithms. Fatigued data in acceleration and plantar pressure were obtained from a wearable insole device after subjects performed a fatiguing manual rebar tying activity. The classification performance was assessed using evaluation metrics and confusion matrix.

Table 3 illustrates the classification performance (i.e., correctly classified samples at a window segment of 2.56 s) for different types of supervised machine learning algorithms. As indicated in Table 3, both training and 10-fold cross-validation accuracies were shown to predict the performance of a trained model. Cross-validation results show that the best classification performance was achieved by the RF algorithm with an accuracy of 86%. Although KNN (i.e., 77.4%) and SVM (i.e., 72.5%) also showed comparable classification performance, the lowest classification performance was obtained by ANN algorithm with an accuracy of 57.4%. Similar results were found for the training accuracies of the algorithms, showing the RF algorithm as the best algorithm for identifying physical fatigue levels based on wearable insole data. In summary, the RF algorithm achieved the best classification performance (86%), followed by the KNN, SVM, DT, and ANN algorithms. Our results showed similar classification performance in previous studies on activity and fall detection recognition, indicating that the RF algorithm achieved better performance accuracy than other algorithms [46, 51, 67, 68]. Arif and Kattan [67] used acceleration sensors to identify 12 different types of physical activities, showing a classification accuracy of 98% obtained by the RF algorithm. By collecting acceleration data, Cha et al. [68] proved the feasibility of distinguishing static and non-static office activities. They reported that the RF algorithm obtained the highest classification accuracy of 96.1% with a window segment of 4 s. Antwi-Afari et al. [51] used the RF algorithm with a window segment of 0.32s to identify employees' loss of balance events based on plantar pressure patterns and reported a classification accuracy of 97%. In another study, Antwi-Afari et al. [46] explored the use of acceleration and plantar pressure data for overexertion-related activities. They reported that RF algorithm achieved the best classification performance with an accuracy of 98.3% at a 2.65 s window segment. It is widely known that the RF algorithm is an ensemble algorithm that can reduce computational time and mitigate overfitting [69]. Consequently, the results showed that acceleration and plantar pressure data collected from a wearable insole device can identify workers' physical fatigue levels after conducting a manual rebar tying activity. Taken together, the RF algorithm could be utilized to detect and classify physical weariness, which would help improve safety and productivity amongst workers.

Table 3. Classification performance of different types of algorithms

Supervised machine learning algorithms	Training accuracy (%)	10-fold cross-validation (%)
Artificial Neural Network (ANN)	58.20	57.40
Decision Tree (DT)	67.60	66.40
Random Forest (RF)	87.70	86.00
K-Nearest Neighbor (KNN)	78.80	77.40
Support Vector Machine (SVM)	73.90	72.50

The confusion matrix and performance evaluation metrics of three sub-classification problems, namely: PFL1, PFL2, and PFL3 using the best algorithm (i.e., RF algorithm) with a window segment of 2.65 s were presented in Tables 4, 5, and 6 respectively. The PFL1 sub-classification problem, as presented in Table 4 achieved the highest performance of the RF algorithm for classifying physical fatigue levels. For precision metric, the RF algorithm achieved classification performance of 98.18% and 95.95% for NLPF and LLPF, MLPF, HLPF classes, respectively. Between the two classes, the highest recall value was 98.61% for the physically fatigued class (i.e., LLPF, MLPF, HLPF). In addition, the highest values of specificity and F1-score for PFL1 sub-classification were 98.61% and 97.62%, respectively. As shown in Table 4, the classification accuracy of the RF algorithm for PLF1 sub-classification was 96.90%. Taken together, these results indicate a high reliability of identifying workers' physically fatigued states based on the proposed framework. However, it may not be useful to correctly identify workers' high-level fatigue using PLF1 sub-classification since it combines different levels of physical fatigued patterns. Nevertheless, it is remarkable that fewer misclassified data samples were found between the two classes of PLF1 sub-classification performance (Table 4).

Table 4. Confusion matrix and performance evaluation for random forest (RF) during PLF1 sub-classification

		Predicted class		Precision	Recall	Specificity	F1-score	Accuracy
True class	NLPF	539	30	98.18	94.73	98.61	96.42	96.90
	LLPF, MLPF, HLPF	10	710	95.95	98.61	94.73	97.26	
		NLPF	LLPF, MLPF, HLPF					

Note: NLPF = no-level physical fatigue (Borg's RPE score of 6); LLPF = low-level physical fatigue (Borg's RPE score of 7-11); MLPF = medium-level physical fatigue (Borg's RPE score of 12-16); and HLPF = high-level physical fatigue (Borg's RPE score of ≥ 17)

As presented in Table 5, the highest values of precision, recall, specificity, and F1-score were 94.51%, 93.48%, 96.98%, and 93.99%, respectively. It was found that these highest evaluation metrics belong to no-level physical fatigue class, indicating that acceleration and plantar pressure data collected from a wearable insole device have a higher potential in identifying no-level physical fatigue class than other classes. The classification accuracy of the RF algorithm for PLF2 sub-classification was 94.05%. This classification accuracy of PLF2 sub-classification was less than PLF1 sub-classification. The decrease in classification accuracy of PLF2 sub-classification may be attributed to more classes for classification performance. In addition, Table 5 shows more confusion between classes. Specifically, it was found that the most confused classes were low-level physical fatigue and high-level physical fatigue. It classified 35 low-level physical fatigued data samples as high-level physical fatigued data samples. These confusing results could be explained by the fact that similar acceleration and plantar pressure data were collected during PLF2 sub-classification.

Table 5. Confusion matrix and performance evaluation for random forest (RF) during PLF2 sub-classification

		Predicted class			Precision	Recall	Specificity	F1-score	Accuracy
True class	NLPF	430	20	10	94.51	93.48	96.98	93.99	94.05
	LLPF	15	350	35	88.61	87.50	94.94	88.05	
	HLPF	10	25	394	89.75	91.84	94.77	90.78	
		NLPF	LLPF	HLPF					

Note: NLPF = no-level physical fatigue (Borg's RPE score of 6); LLPF = low-level physical fatigue (Borg's RPE score of 7-11); and HLPF = high-level physical fatigue (Borg's RPE score of ≥ 17)

Table 6 presented the results of classifying all levels of physical fatigue using RF algorithm. Generally, the evaluation metrics of RF algorithm for PLF3 sub-classification achieved the lowest performance than both PLF1 and PLF2 sub-classification problems. The precision of RF algorithm for PLF3 sub-classification achieved a performance rate between 52.63% to 82.62% (Table 6). The specificity and F1-score metrics of RF algorithm for PLF3 sub-classification range from 89.60% to 92.33% and 52.63% to 83.46%, respectively. In summary, the highest values of precision, recall, specificity, and F1-score for PLF3 sub-classification were 82.62%, 84.32%, 92.33%, and 83.46%, respectively. These highest values of evaluation metrics for PLF3 sub-classification were attributed to no-level physical fatigue class. Nonetheless, it was reported that no-level physical fatigue class (84.32%) had the most positive instances (i.e., recall) on the performance of RF algorithm, followed by high-level physical fatigue (74.18%), low-level physical fatigue (68.18%), and medium-level physical fatigue (52.63%) classes. The overall classification accuracy of the RF algorithm for PLF3 sub-classification was 86%. These results indicate that a wearable insole device is reliable for identifying and classifying workers' physical fatigue levels using acceleration and plantar pressure data. Consequently, these findings show that the proposed approach can serve as a preventive measure for monitoring and reducing the risk of developing physical fatigue after a manual rebar tying activities. As shown in Table 6, the PFL3 sub-classification had the highest level of confusion compared to PLF1 (Table 4) and PLF2 (Table 5) sub-classification problems. It was found that the top two most confused classes are medium-level physical fatigue and high-level physical fatigue. Specifically, 52 high-level physical fatigued data samples were misclassified as medium-level physical fatigued data samples (Table 6). These misclassified data samples between medium-level physical fatigue and high-level physical fatigue classes may be due to increasing the number of classes (i.e., four levels of RPE) for PLF3 sub-classification performance. Most importantly, there was little confusion in data samples between no-level physical fatigue and high-level physical fatigue classes, indicating the feasibility of classifying workers' physical fatigue based on the proposed framework.

Table 6. Confusion matrix and performance evaluation for random forest (RF) during PLF3 sub-classification

		Predicted class				**Precision**	**Recall**	**Specificity**	**F1-score**	**Accuracy**
True class	NL PF	328	32	18	11	82.62	84.32	92.33	83.46	86.00
	LL PF	35	210	38	25	67.31	68.18	89.60	67.74	
	ML PF	20	42	120	46	52.63	52.63	89.82	52.63	
	HL PF	14	28	52	270	76.70	74.18	91.14	75.42	
		NL PF	LL PF	ML PF	HL PF					

Note: NLPF = no-level physical fatigue (Borg's RPE score of 6); LLPF = low-level physical fatigue (Borg's RPE score of 7-11); MLPF = medium-level physical fatigue (Borg's RPE score of 12-16); and HLPF = high-level physical fatigue (Borg's RPE score of ≥ 17)

Automated identification and classification of physical fatigue have been widely studied [52, 70, 71]. Janssen et al. [70] came up with a machine-learning model to characterize gait patterns prior to, during, and after complete leg exhaustion caused by isokinetic leg exercises. Their results reported a classification accuracy of 98.1%. Karvekar et al. [52] proposed a machine-learning model to identify human physical fatigue levels by collecting motion signals from a WIMU embedded in a smartphone after performing a squatting fatiguing exercise. By adopting different types of SVM algorithms, classification accuracy scores of 91 percent, 78 percent, and 64 percent were found for 2-class, 3-class, and 4-class, respectively. Although these previous studies achieved higher classification performance, the fatiguing protocols are mainly exercise-induced experiments, which have limited application in industrial settings such as construction.

In the construction field, numerous research studies have been conducted to identify workers' physical fatigue [23, 34; 44, 72]. Aryal et al. [23] investigated real-time monitoring of physical fatigue in construction workers using wearable sensors such as heart rate monitors, infrared temperature sensors, and EEG sensors. They achieved a classification accuracy of 82%, implying that workers' physical fatigue can be monitored using extracted features from sensor signals. While Aryal et al. [23] extracted features from physiological sensors during manual handling tasks, the present study extracted similar features from wearable insole sensors during manual rebar tying activity. Physiological sensors such as heart rate monitors, infrared temperature sensors, and EEG sensors are intrusive because these sensors need to be connected to workers' bodies. Yu et al. [34] proposed a novel non-intrusive method to monitor the whole-body physical fatigue of construction workers using computer vision. Their findings provided objective joint-level fatigue assessments during scaffolding and masonry tasks. However, computer vision applications (e.g., RGB cameras) are ineffective for continuous monitoring and are affected by direct sunlight during data collection on real-world construction sites. Zhang et al. [44] applied a machine learning approach to automatically recognize jerk changes due to physical exertion, indicating physical fatigue using WIMU sensors during two bricklaying tasks. They found a classification accuracy of 94% for the wall building experiment and 80% for the first-course experiment. However, physiological metrics (e.g., sEMG, jerk) are more suitable to assess localized muscle fatigue instead of generalized physical fatigue among construction workers [7]. Despite the differences in experimental protocols between previous studies and the present study, they altogether have great capability for measuring real-time physical fatigue in construction workers, thus, mitigating workers' threat of developing musculoskeletal disorders and fall injuries.

Regardless of the great potential of the proposed approach, there are limitations in this study. First, the present study was designed and conducted by a small number of student subjects who performed a manual rebar tying activity in a laboratory setting. Of course, there are differences in human characteristics (e.g., experience, strength level, age, gender, etc.) between students and construction workers. As such, further studies should capture huge samples of data from experienced construction workers (e.g., rebar workers) when they perform similar experimental protocols on construction sites. Such dataset would help to generalize the findings of the proposed approach. Second, the fatiguing protocol used in the current study was a manual rebar tying activity.

Although the simulated fatiguing protocol involves postural orientations and body movements that may result in postural instability, decline in muscle performance, and altered normal movement patterns, there are other fatiguing protocols performed by workers on construction sites. Since a specific fatiguing protocol may result in different risks of developing musculoskeletal disorders and fatigued-related injuries, future studies should conduct other construction-related fatiguing protocols such as bricklaying, roofing, manual repetitive handling tasks, etc. Third, the present study applied a subjective measure (i.e., Borg's RPE score) to identify physical fatigue. Future studies are warranted to incorporate objective physiological measures of physical fatigue such as HR, HRV, ST, EDA, etc. In addition, these physiological data collected from wearable biosensors can be combined with acceleration and plantar pressure data collected from a wearable insole device for data processing and further analyses. Lastly, this study proposed five kinds of supervised machine learning classifiers for classifying physical fatigue levels in construction workers. As explained above, supervised machine learning algorithms require extracting relevant features and manual labelling of raw sensor signals, which are time-consuming, cumbersome, and may affect classification performance. To improve classification performance and model evaluation, future studies should use other time-series data analyses such as unsupervised learning algorithms (e.g., clustering) and deep learning networks (e.g., recurrent neural networks).

4. Conclusions

This study proposed a wearable insole device to identify and classify physical fatigue levels in construction workers. Towards achieving this goal, a fatiguing manual rebar tying activity was conducted by 10 asymptomatic subjects in a laboratory setting. Borg's RPE was used to obtain subjective judgments of levels of physical exhaustion on an ongoing basis. The classification performance of identifying physical fatigue levels was assessed on three sub-classification problems, namely: (1) PFL1: identifying the existence of physical fatigue levels (NLPF vs LLPF, MLPF, HLPF); (2) PFL2: identifying the no-level, low-level, and high-level physical fatigue levels (NLPF vs LLPF vs HLPF); and (3) PFL3: identifying all physical fatigue levels (NLPF vs LLPF vs MLPF vs HLPF). Relevant features were extracted from segmented data, and the classification performance of five algorithms was evaluated using various evaluation metrics. Cross-validation revealed that the RF algorithm (i.e., best algorithm) with a 2.56 s window segment produced the highest accuracy of 86%. In addition, the precision, recall, specificity, and F1-score metrics of the

RF algorithm obtained classification performance between 52.63% to 82.62%, 52.63% to 84.32%, 89.60% to 92.33%, and 52.63% to 83.46%, respectively. These results suggest that fatigued patterns based on acceleration and plantar pressure data captured from a wearable insole device can identify workers' physical fatigue in construction after performing a manual rebar tying activity. The proposed approach will contribute to: (1) non-invasive, continuous monitoring of workers' movements and automated identification of physical fatigue in construction workers; (2) extending wearable sensor-based approaches while addressing the shortfalls in existing approaches for physical fatigue assessment and identification; and (3) assisting construction practitioners to provide proactive measures and useful guidelines (e.g., work-rest schedules) for mitigating fatigue-related injuries and other occupational injuries on construction sites.

Data Availability Statement

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

Author Statement

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Declaration of Competing Interest

None

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