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Automatic Ergonomic Assessment Considering Awkward Posture and External Load

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Abstract

The construction industry is characterized by physically demanding tasks and the adoption of awkward postures, both of which contribute to a high incidence of work-related musculoskeletal disorders (WMSDs). Despite the significance of these factors, few studies considered the external load estimation that considers the actual weights being lifted and carried in ergonomic assessments. This research aims to enhance the accuracy of WMSD risk evaluations by integrating external load estimation into ergonomic assessments. We utilized skeleton tracking technology to automatically evaluate awkward postures based on the Rapid Upper Limb Assessment (RULA) framework, a method for evaluating the exposure of workers to ergonomic risk factors. Concurrently, we analyzed electromyography (EMG) signals measuring muscle activity to extract pertinent features for estimating external loads, which were subsequently integrated into the overall ergonomic assessment. Experimental results demonstrate that the Multi-Layer Perceptron-Back Propagation algorithm outperforms alternative machine learning classification methods, achieving an accuracy rate of 98.3%.

1 Introduction

Construction workers frequently encounter challenging physical conditions, such as prolonged exposure to uncomfortable postures and the necessity of lifting and transporting heavy materials (Park et al., 2018). These adverse conditions related to ergonomic risk factors not only heighten the possibility of developing Work-Related Musculoskeletal Disorders (WMSDs) but also result in increased error rates and a decline in overall productivity (Li et al., 2024). Consequently, it is imperative to systematically evaluate the ergonomic risks associated with various construction activities for enhancing health and safety management practices, ultimately contributing to the sustainable development of the construction industry (Liao et al., 2023).

Among the various methodologies employed to measure exposure to WMSD risks, posture-based ergonomic assessment stands out as one of the most widely utilized techniques (Janowitz et al., 2006). Traditional methods of manual observation involve an ergonomist who observes workers' postures and movements in real-time or through recorded video footage and then assigns scores with ergonomic assessment tool (Lowe et al., 2014). However, these manual observation techniques are often criticized for being labor-intensive and time-consuming, demanding substantial effort and susceptible to observer bias (Seo & Lee, 2021), which hinders the efficiency and reliability of ergonomic assessments in dynamic construction environments. In response to these limitations, recent advancements in ergonomic assessment have sought to employ wearable sensors and vision-based method to automate the recognition of potentially hazardous postures during ongoing tasks (Wang et al., 2015). Wearable sensor systems, such as joint angle measurement systems (Rodrigues et al., 2022) and inertial measurement units (IMUs) (Yan et al., 2017), typically concentrate on monitoring specific joints and movements. The focus on isolated joints may overlook how various body segments interact during complex tasks. Vision-based methods offer a more holistic approach to ergonomic assessment by evaluating the entire configuration of the body. Yu et al. (2019b) and Roberts et al. (2020) explored innovative approaches to three-dimensional (3D) pose estimation by utilizing two-dimensional (2D) video inputs. With advancements in technology that can capture joint and activity information in real-time, Lin et al. (2022) developed a system that automatically selects appropriate assessment scales and calculates risk scores using image-based motion capture techniques. Hossain et al. (2023) employed deep learning techniques to predict ergonomic risk levels by analyzing 3D coordinates of human body positions.

Despite the substantial body of research dedicated to posture estimation, the consideration of external load in ergonomic assessments is often overlooked. This oversight is particularly significant in construction settings, where workers frequently engage with external loads. Some studies (Fortini et al., 2020; Lorenzini et al., 2019; Ventura et al., 2021) have explored external loads with the focus on individual body joints, which may fail to capture the broader implications of external loads on the worker's entire musculoskeletal system. Yu et al. (2019a) developed a smart insole to estimate external load by using total weight minus the worker’s self-weight. However, it assumes that all external load is transmitted through the feet, rendering it ineffective for postures such as leaning against walls or sitting on the ground. In contrast, electromyography (EMG) offers a more comprehensive solution, as it offers insights into muscle activation patterns and the physiological demands placed on the body (Wang et al., 2015). By quantifying the electrical activity of muscles, EMG can provide a clear understanding of how external loads affect worker performance across various postures. Recent research by Kumari et al. (2023) exemplifies the potential of EMG in this context. Their analysis of EMG data focused on agricultural workers engaged in pushing and pulling operations, revealing significant changes in muscle activity corresponding to varying external loads. This approach highlights the utility of EMG in capturing the dynamic relationship between external loads and muscle engagement, offering a more nuanced understanding of ergonomic stressors.

Our study proposes a framework that combines skeleton tracking technology with EMG signals to deliver a comprehensive assessment of worker well-being. By employing skeleton tracking, the system captures the 3D coordinates of body joints and employs the Rapid Upper Limb Assessment (RULA) method for automatic evaluation of human posture and movement. Concurrently, the analysis of EMG signals provides critical insights into the estimation of external loads placed on workers. This study will examine 40 widely utilized electromyography (EMG) features to identify the optimal combination that most accurately reflects external load. By integrating EMG analysis into ergonomic assessments, the framework enhances the monitoring of ergonomic risks and alerts workers to the potential risks of overexertion before injuries occur. Section 2 provides details of our proposed method to monitor ergonomic and estimate external load. The experimental design and results will be presented in Section 3, while the discussion will be illustrated in Section 4. The conclusion will be finally drawn in Section 5.

2 Method

2.1 Ergonomic Assessment

RULA is a widely recognized framework for evaluating ergonomics that aims to identify potentially harmful postures and movements that could contribute to the development of WMSDs (Nayak & Kim, 2021). RULA considers biomechanical and postural load requirements of job demands on the neck, trunk, and upper extremities. By using RULA, employers can take proactive steps to manage the risks associated with MSDs, creating a safe and comfortable work environment for workers.

Despite its utility, the RULA assessment has significant limitations, particularly in dynamic and fast-paced environments like construction sites. Since RULA only allows the evaluator to assess worker's posture at one point in time, it usually selects the representative postures, like the most difficult postures based on the worker interview and initial observation, or postures maintained for the longest period, or postures where the highest force loads occur (Middlesworth, 2012). The assessment generally involves analyzing a static image of the chosen posture, which can take approximately 10 to 20 minutes, depending on the complexity of the task being performed. However, construction workers frequently change their postures and perform a variety of tasks quickly, making it difficult for evaluators to capture an accurate representation of ergonomic risks at any single moment. This static approach can lead to incomplete assessments and may overlook critical factors affecting worker safety and comfort. Therefore, our method aims to enhance this process by automatically calculating the RULA score, allowing for more efficient and timely instructions. The model proposed in this project can detect real-time motion of human and generate 3D-coordinate of 32 joints. The joint data can subsequently be visualized in the form of a skeletal representation and used to evaluate the ergonomic level automatically based on RULA.

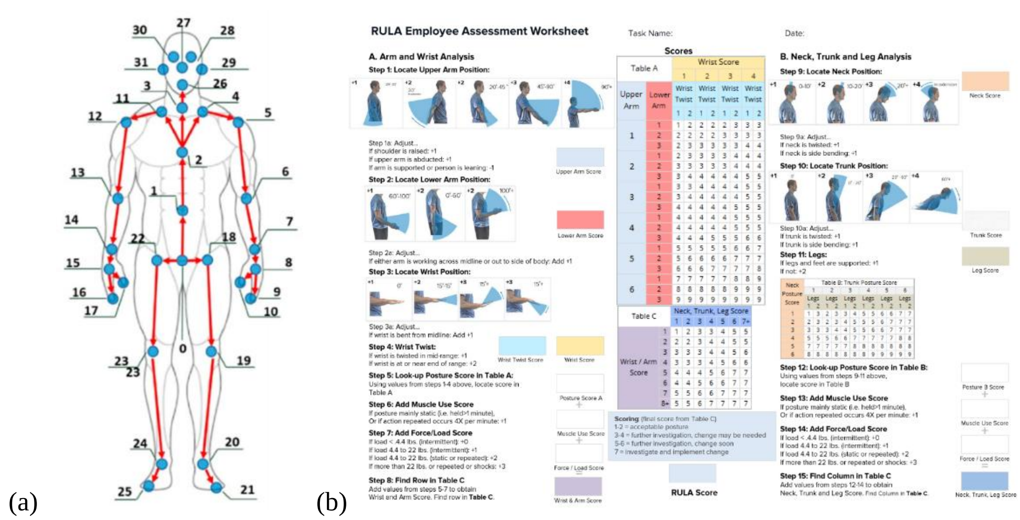


Figure 1: (a) Human Skeleton Model (b) RULA

Azure Kinect developed by Microsoft is capable of capturing depth images and tracking skeletal joints, allowing for the representation of position and orientation in three-dimensional space (Ahad et al., 2021). The skeleton data consists of a set of P joints $J = [J_1, J_2, J_3, \ldots, J_P]$ where P equals to the number of joints. In our method, the dataset contains 32 joints, as shown in Figure 1(a). We calculated a position-based kinematics feature vector for every skeleton frame, with each joint denoted as a three-dimensional vector $J_i = [J_{i_x}, J_{i_y}, J_{i_z}]$ within the Kinect coordinate system. The skeleton vector $\boldsymbol{v}$ be calculated by subtracting the coordinates of the final joint point J_F from the initial joint point J_S. Some RULA criteria are determined by analyzing the amplitude of body segment movement, such as the swing of upper arm, as shown in Figure 1(b). In the Azure coordination, there are three directions of vectors $\boldsymbol{v_i} = \{\boldsymbol{v_x}, \boldsymbol{v_y}, \boldsymbol{v_z}\}$. The amplitude of movement can be represented as the angle between the skeleton vector and direction of vector, calculated by Equation (1).

$$\cos(\theta) = \frac{\boldsymbol{v} \cdot \boldsymbol{v_i}}{|\boldsymbol{v}||\boldsymbol{v_i}|} \tag{1}$$

When assessing the upper arm position, humans are supposed to stand on the planes parallel to x-z plane according to the coordinate systems in the depth camera. The direction of vector $\boldsymbol{v_i}$ should be $\boldsymbol{v_y}$ that is $[0, 1, 0]$. The vector of left upper arm $\boldsymbol{v}$ can be determined by subtracting the coordinates of the final point of left elbow from the initial point of left shoulder. The score of left upper arm will be one from 20-degree extension to 20-degree flexion $(20 \leq \theta)$. The score of left upper arm will be two for 20-to-45-degree extension or flexion $(20 < \theta \leq 45)$. The score of left upper arm will be three for 45-to-90-degree extension or flexion (45$< \theta \leq 90$). The score of left upper arm will be three for more than 90-degree extension or flexion $(90 < \theta)$.

2.2 Classification Method

In this study, we frame the estimation of external load as a classification problem, employing electromyography (EMG) features as input variables to explore robust classification techniques. Our objective is to effectively categorize the EMG signals into three distinct load levels: 0 kg, 2 kg, and 5 kg. The integration of machine learning algorithms into this framework enhances the capacity to detect and classify high-dimensional data, facilitating a systematic analysis of the complex patterns inherent in the EMG signals. Given the variability of signal patterns caused by external influences, such as changes in electrode positioning, classifiers are particularly well-suited to manage these fluctuations and mitigate the risk of overfitting (Asghari & Hu, 2007). To address the requirements for real-time processing and long-term operation, we will compare several advanced classification methods, including Multi-Layer Perceptron-Back Propagation (MLP-BP) neural networks (Reyes-Fernandez et al., 2024), K-Nearest Neighbors (KNN) (Bukhari et al., 2020), and Support Vector Machine (SVM) (Liu et al., 2021).

(1) MLP-BP

MLP, as a type of artificial neural network, can establish mathematical models through a finite number of iterations, which suits the study of complex nonlinear characteristics (Dellacasa Bellingegni et al., 2017). It contains three types of layers: the input layer to present data to the network, hidden layer to perform weight vector computation on input data, and output layer to predict the response value. Each layer is composed of different numbers of neurons, and the number of neurons in the input layer and output layer corresponds to the number of variables. The number of hidden layers and neurons in hidden layers plays an imperative role in the output response. MLP uses the BP algorithm to train the network by propagating the error back through the layers of the network and adjusting the weights and biases of each neuron in the network, such that the error is minimized (Kotsiantis, 2007). MLP-BP has advantages in its accuracy and its excellent generalization capability, which can deal with incomplete, noisy, and fuzzy data (Kukreja et al., 2016). Meanwhile, it belongs to computationally intensive algorithms, which are time-consuming.

(2) KNN

The fundamental principle of KNN is that classification of unknown instances can be implemented by relating the unknown to the known based on some distance function (Paul et al., 2017). KNN algorithm finds the K-nearest neighbors to the unknown instance, and the label of the unknown instance is allocated according to the majority vote of the K-nearest neighbors. It can be considered as two stages: a) use Euclidean distance to make pre-grouping of data and create subclusters and b) use a similar measure to merge the subclusters hierarchically (Rechy-Ramirez & Hu, 2011). As a non-parametric algorithm, KNN is intuitive and easy to implement. Without training steps, new data can be added seamlessly, which allows a quick respond to changes in the input. Nevertheless, due to computation complexity and memory limitation, KNN has poor performance of large dataset and high dimensionality (Soofi & Awan, 2017).

(3) SVM

SVM is a statistical learning system for classification and regression analysis, which is essentially to determine a hyperplane or a boundary that separates the training data into classes (Subasi, 2013). New measured data is then stored and fed back to the model so that the influence of unknown disturbances frequently appeared in the process can be compensated, which improves the accuracy and achieves self-optimization. SVM is applicable not only to training data with many features relative to the number of training instances (Kotsiantis, 2007), but also to a wide range of classification problems such as high dimensional and not linearly separable problems. However, SVM will be limited to the dataset with more data or noise.

2.3 Load Estimation Based on EMG Features

Electromyography (EMG) is an instrument that allows the measurement and analysis of the electrical signals that are produced by muscle activity. Reaz et al. (2006) illustrated that a muscle is composed of bundles of specialized cells capable of contraction and relaxation. Skeletal muscle attaches to the bone, as one of the three significant muscle tissues, consists of thousands of muscle fibers wrapped together by connective tissue sheaths. Skeletal muscle can receive and respond to stimuli. Its contraction is initiated by electrical impulses that travel between the central and peripheral nervous systems and muscles, which facilitates the support and movement of the skeleton. When skeletal muscles contract, the electrical activity of the muscle fibers active can be detected by surface electrodes. After amplification, filtering, and processing, EMG signals can be acquired, which provides information about muscle function, like muscle activation and muscle recruitment patterns.

In this study, EMG is used to provide a estimation of external load. Due to the enormous number of inputs and randomness of the EMG signal, it is impractical to feed the raw signals to a classifier directly (Asghari & Hu, 2007). Feature extraction converts the raw signals acquired into a relevant data structure by eliminating background noise and highlighting the important data (Rechy-Ramirez & Hu, 2011). The investigation of feature extraction characteristics in both the time domain and frequency domain has gained significance in the classification of EMG signals (Phinyomark et al., 2012). 40 feature extraction methods that are widely applied are introduced in Table 1.

no	Symbol	Feature Description	Equation
1	IEMG	Integrated EMG	$\mathrm{IEMG} = \sum_{i=1}^{N} \lvert x_i \rvert$
2	MAV	Mean Absolute Value	$\mathrm{MAV} = \frac{1}{N} \sum_{i=1}^{N} \lvert x_i \rvert$
3	MMAV	Modified Mean Absolute Value	$\mathrm{MMAV} = \frac{1}{N} \sum_{i=1}^{N} w_i \lvert x_i \rvert$ $w_i = \begin{cases} 1, & \text{if } 0.25N \le i \le 0.75N \\ 0.5, & \text{otherwise} \end{cases}$
4	MMAV2	Modified Mean Absolute Value 2	$\mathrm{MMAV2} = \frac{1}{N} \sum_{i=1}^{N} w_i \lvert x_i \rvert$

			$w_i = \begin{cases} 1, & \text{if } 0.25N \le i \le 0.75N \\ \frac{4i}{N}, & \text{elseif } i < 0.25N \\ \frac{4(i-N)}{N}, & \text{otherwise} \end{cases}$
5	SSI	Simple Square Integral	$\mathrm{SSI} = \sum_{i=1}^{N} {x_i}^2$
6	VARE	Variance of EMG	$\mathrm{VARE} = \frac{1}{N-1}\sum_{i=1}^{N} {x_i}^2$
7	TM	Temporal Moment	$\mathrm{TM} = \left\lvert \frac{1}{N}\sum_{i=1}^{N} {x_i}^3 \right\rvert$
8	RMS	Root Mean Square	$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} {x_i}^2}$
9	VO	V-Order	$x_i = (\gamma {m_i}^{\alpha}) n_i$ $\mathrm{VO} = (\frac{1}{N}\sum_{i=1}^{N} {x_i}^{v})^{\frac{1}{v}}$
10	LD	Log Detector	$\mathrm{LD} = e^{\frac{1}{N}\sum_{i=1}^{N} \log(\lvert x_i \rvert)}$
11	WL	Waveform Length	$\mathrm{WL} = \sum_{i=1}^{N-1} \lvert x_{i+1} - x_i \rvert$
12	AAC	Average Amplitude Change	$\mathrm{AAC} = \frac{1}{N}\sum_{i=1}^{N-1} \lvert x_{i+1} - x_i \rvert$
13	DASDV	Difference Absolute Standard Deviation Value	$\mathrm{DASDV} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1} (x_{i+1} - x_i)^2}$
14	ZC	Zero Crossing	$\mathrm{ZC} = \sum_{i=1}^{N-1} [\mathrm{sgn}(x_i \times x_{i+1}) \cap \lvert x_i - x_{i+1} \rvert \ge \text{threshold}]$; $\mathrm{sgn}(x) = \begin{cases} 1, & \text{if } x \ge \text{threshold} \\ 0, & \text{otherwise} \end{cases}$
15	MYOP	Myopulse Percentage Rate	$\mathrm{MYOP} = \frac{1}{N}\sum_{i=1}^{N} [f(x_i)]$; $f(x) = \begin{cases} 1, & \text{if } \lvert x \rvert \ge \text{threshold} \\ 0, & \text{otherwise} \end{cases}$
16	WA	Willison Amplitude	$\mathrm{WA} = \sum_{i=1}^{N-1} [f(\lvert x_i - x_{i+1} \rvert)]$; $f(x) = \begin{cases} 1, & \text{if } x \ge \text{threshold} \\ 0, & \text{otherwise} \end{cases}$
17	SSC	Slope Sign Change	$\mathrm{SSC} = \sum_{i=2}^{N-1} \left[f[(x_i - x_{i-1}) \times (x_i - x_{i+1})] \right]$; $f(x) = \begin{cases} 1, & \text{if } x \ge \text{threshold} \\ 0, & \text{otherwise} \end{cases}$
18	SKEW	Skewness	$\mathrm{SKEW} = \frac{M_3}{M_2}\sqrt{M_2}$ $M_k = \frac{1}{N}\sum_{i=1}^{N} (x_i - \bar{x})^k$
19	KURT	Kurtosis	$\mathrm{KURT} = \frac{M_4}{M_2 M_2}$
20	MFL	Maximum Fractal Length	$\mathrm{MFL} = \log_{10}(\sqrt{\sum_{i=1}^{N-1} (x_{i+1} - x_i)^2})$
21	DVARV	Difference Variance Value	$\mathrm{DVARV} = \frac{1}{N-2}\sum_{i=1}^{N-1} (x_{i+1} - x_i)^2$
22	IQR	Interquartile Range	$\mathrm{IQR} = Q_3 - Q_1$
23	MAD	Mean Absolute Deviation	$\mathrm{MAD} = \frac{1}{N}\sum_{i=1}^{N} \lvert x_i - \bar{x} \rvert$
24	AR	Auto-Regressive Model	$x_i = -\sum_{p=1}^{P} a_p x_{i-p} + w_i$
25	AE	Average Energy	$\mathrm{AE} = \frac{1}{\mathrm{N}}\sum_{i=0}^{N-1} {x_i}^2$
26	VAR	Variance	$\mathrm{VAR} = \frac{1}{N-1}\sum_{i=1}^{N} (x_i - \bar{x})^2$
27	SD	Standard deviation	$\mathrm{SD} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} (x_i - \bar{x})^2}$
28	CARD	Cardinality	$y_i = sort\ (x_i)$

			$\mathrm{CARD} = \sum_{i=1}^{N-1} \lvert y_i - y_{i+1} \rvert$, if $\lvert y_i - y_{i+1} \rvert >$ threshold
29	EMAV	Enhanced Mean Absolute Value	$\mathrm{EMAV} = \frac{1}{N} \sum_{i=1}^{N} \lvert {x_i}^p \rvert$ $p = \begin{cases} 0.75, & \text{if } 0.2N \le i \le 0.8N \\ 0.5, & \text{otherwise} \end{cases}$
30	EWL	Enhanced Wavelength	$\mathrm{EWL} = \sum_{i=2}^{N} \lvert (x_i - x_{i-1})^p \rvert$ $p = \begin{cases} 0.75, & \text{if } 0.2N \le i \le 0.8N \\ 0.5, & \text{otherwise} \end{cases}$
31	NZC	New Zero Crossing	$\mathrm{NZC} = \begin{cases} 1, & \text{if } x_i > \text{threshold and } x_{i+1} < \text{threshold} \\ & \text{or } x_i < \text{threshold and } x_{i+1} > \text{threshold} \\ 0, & \text{otherwise} \end{cases}$ $\text{threshold} = 4(\frac{1}{10} \sum_{i=1}^{10} x_i)$
32	ASS	Absolute value of the Summation of Square Root	$\mathrm{ASS} = \left\lvert \sum_{i=1}^{N} (x_i)^{1/2} \right\rvert$
33	MSR	Mean value of the Square Root	$\mathrm{MSR} = \frac{1}{N} \sum_{i=1}^{N} (x_i)^{1/2}$
34	ASM	Absolute Value of Summation of the expth root	$\mathrm{ASM} = \lvert \sum_{i=1}^{N} (x_i)^{exp} \rvert$ $exp = \begin{cases} 0.75, & \text{if } 0.25N \le i \le 0.75N \\ 0.25, & \text{otherwise} \end{cases}$
35	DAMV	Difference Absolute Mean Value	$\mathrm{DAMV} = \frac{1}{N-1} \sum_{i=1}^{N-1} \lvert x_{i+1} - x_i \rvert$
36	LDAMV	Log Difference Absolute Mean Value	$\mathrm{LDAMV} = \log\left(\frac{1}{N-1} \sum_{i=1}^{N-1} \lvert x_{i+1} - x_i \rvert\right)$
37	LDASD V	Log Difference Absolute Standard Deviation	$\mathrm{LDASDV} = \log \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (x_{i+1} - x_i)^2}$
38	COV	Coefficient of Variation	$\mathrm{COV} = \frac{\sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (x_i - \bar{x})^2}}{\frac{1}{N} \sum_{i=1}^{N-1} x_i}$
39	LCOV	Log Coefficient of Variation	$\mathrm{LCOV} = \log \frac{\sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (x_i - \bar{x})^2}}{\frac{1}{N} \sum_{i=1}^{N-1} x_i}$
40	LTKEO	Log Teager Kaiser Energy Operator	$\mathrm{LTKEO} = \log \sum_{i=0}^{N-2} ({x_i}^2 - x_{i-1} x_{i+1})$

Table 1: EMG Feature and Equation

3 Experiments and Results

3.1 Experiment Design

To examine the feasibility of the EMG-based parameters in classifying workers' external loads, we conducted an experiment and recorded the electrical activity of 10 healthy subjects while performing tasks with different external loads. 5 males and 5 females were randomly selected, aged between 19 and 22 years old. The surface of the collection site (skin) was cleaned with alcohol and coated with glycerin or conductive paste to reduce skin surface impedance and enhance electrical conductivity.

Subjects were asked to stand with the upper arm perpendicular to the ground without the abduction or adduction while the lower arm parallel to the ground without the extension or flexion, as

Figure 2 shown below. Three tasks required subjects to carry 0 kg, 2 kg, and 5 kg on their hands respectively. Subjects were asked to maintain the posture for around 6 seconds for one exercise. EMG data were collected after carrying the weight, which meant that the record did not include the process of putting up or down. A short period of rest was provided between each exercise to mitigate the cascading effect of fatigue. In total we collected 10 subjects × 3 exercises × 4 repetitions = 120 EMG recordings.

(a)  (b) 

Figure 2: (a) Posture of the Subject (b) Positions of Surface Electrode

3.2 Experiment Results

(1) Pose Estimation Results

The automatic ergonomic assessment system has successfully implemented the real-time skeleton monitoring and visualization techniques to evaluate an individual's posture and movement dynamics, shown in Figure 3. This approach facilitates simultaneous monitoring of both the left and right sides of the body, and then selecting the higher score for the overall ergonomic assessment. Throughout the assessment process, essential metrics such as joint angles, posture deviations, and movement patterns are meticulously evaluated and presented in an intuitive format, enhancing the comprehension of ergonomic status.

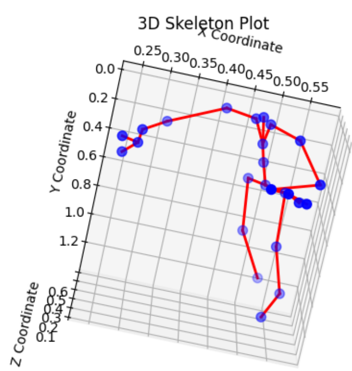
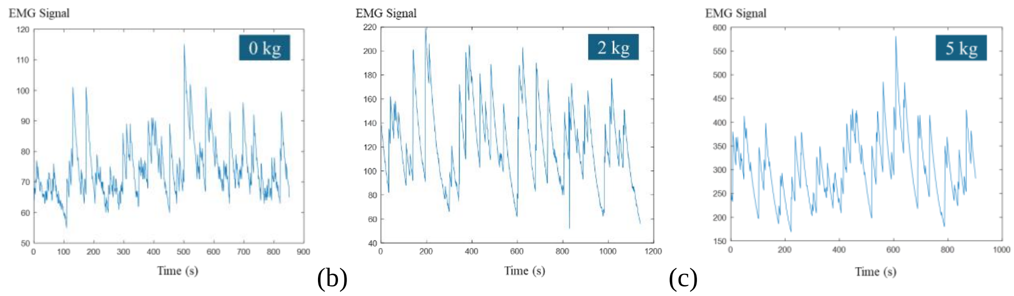


Figure 3: 3D Skeleton Plot

(2) Load Estimation Results

The surface EMG signals collected will inevitably be mixed with noise which can cause invalid features and disturb the classification. Three main types of noise in surface EMG signals include the inherent noise of the electronic components (0 to several kHz), power frequency interference (50 Hz or 60 Hz), and the baseline to drift (0 to 20 Hz) (Li et al., 2020). Therefore, preprocessing is required to denoise signals and enhance feature extraction. Bandwidth of 20 to 500 Hz Bandpass filter and 50 Hz notch filter were applied in this study to remove noise interference. The EMG signal output when the subjects carry different weight is shown in Figure 4.



(a) (b) (c)

Figure 4: EMG Output with (a) 0 kg (b) 2 kg (c) 5kg

The processing of redundant and irrelevant features can diminish model accuracy while also prolonging execution time during classification tasks. To mitigate these issues, a feature selection algorithm is employed between the feature extraction and classification phases, allowing for the automatic identification of critical features (Baby et al., 2021). Our study utilized the Extra Trees classifier to discern the most significant features from the original set. This ensemble learning method enhances the tree splitting technique by reducing the variances inherent in many tree-based and neural network algorithms (Ossai & Wickramasinghe, 2022). Each tree is constructed from the original dataset. At each test node, extra tree is provided with a random sample of k features in that each decision tree selects the most relevant feature to split the data according to the Gini index, which assists the further formulation of multiple de-correlated decision trees (Sharma et al., 2022). Ultimately, all features are ranked in descending order according to their Gini index scores, from which a specified number of top features is selected based on their importance. In this study, 0 kg, 2 kg, and 5 kg were labeled with No-Load, Little-Load, and High-Load respectively. With the extra tree classifier, seven features with the most importance were selected: MSR, LD, CARD, SKEW, EMAV, ASM, LDASDV, as shown in Figure 5.

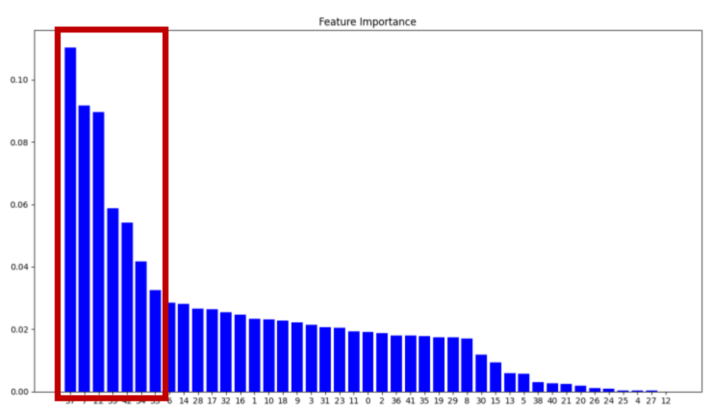


Figure 5: Feature Selection

Given the available data, 84 trials were fed in for training while the remaining 36 trials were used for testing. In this study, MLP-BP had 7 neurons in the input layer that was equal to the number of features selected and 3 neurons for output layer that was the same as the number of labels. MLP-BP applied two hidden layers: the first layer had 30 neurons, and the second layer had 10 neurons. For this configuration, the Rectified Linear Unit (ReLU) activation function and sigmoidal activation function were used in the hidden and output layers respectively. The accuracy of MLP-BP model achieved 98.3% compared with KNN (94.4%) and SVM (97.2%).

(3) Ergonomic Assessment Considering Awkward Posture and External Load

The system is designed to automatically evaluate the ergonomic score for each body part based on the assessed posture of the worker. This evaluation process incorporates both the individual scores derived from body positioning and the estimated external load levels experienced during tasks. By integrating these two critical factors, the system provides a more comprehensive ergonomic assessment. The final score is determined using the RULA worksheet, which systematically evaluates the combined effects of awkward postures and external loads. This holistic approach not only highlights potential risks associated with specific postures but also addresses the impact of external loads on overall worker well-being. Consequently, the resulting ergonomic score serves as a valuable tool for identifying areas that may require intervention, ultimately promoting safer and more efficient work practices.

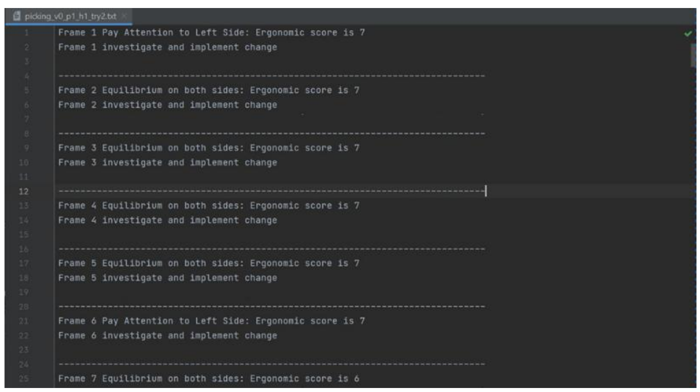


Figure 6: Ergonomic Assessment Result

4 Discussion

By evaluating external load levels, the system can effectively identify instances of overloading and encourage workers to seek assistance as needed, thereby enhancing their overall well-being and minimizing the risk of injury. Furthermore, incorporating external load assessments into the RULA framework significantly enriches the evaluation of ergonomic risk factors. While traditional ergonomic assessments primarily focus on postural evaluation and movement patterns, the integration of load variables offers a more comprehensive understanding of the physical demands placed on workers. This holistic approach leads to a more nuanced and accurate assessment of ergonomic risks, facilitating the design of targeted interventions that can mitigate these hazards and ultimately foster a safer and more productive work environment.

The ergonomics model developed in this study can be seamlessly integrated with a digital display, providing real-time feedback on the ergonomic status for each assessment frame. For instance, when scores reach 5 or 6, the system indicates that further investigation and adjustments are necessary, prompting the display to alert the worker with a yellow light. A score of 7 signifies an urgent need for intervention, triggering a red-light alert. Additionally, the system can identify which side of the body presents greater ergonomic risks, enabling targeted corrective actions.

5 Conclusions

In this study, we present a framework that combines skeleton tracking technology with EMG signals to provide a thorough assessment of worker well-being. Skeleton tracking provided 3D coordinates of body joints and achieved automated evaluation of human posture and movement. This research also selected seven EMG features that are most pertinent to external load classification through Extra Trees classifier. By analyzing these features, we can effectively estimate external load levels in real time, thereby enhancing the ergonomic assessment process. Our results indicate that the MLP-BP algorithm outperforms alternative classification methods, achieving an exceptional accuracy rate of 98.3%. This finding highlights the potential of advanced machine learning techniques to improve safety and efficiency in HRC.

However, this research has limitations regarding the experimental setting, which was conducted in a controlled laboratory environment. While this setting allows for precise measurement and analysis, it may not fully capture the complexities and variabilities present in real-world scenarios. Future studies should aim to conduct field experiments to validate the framework under diverse working conditions, accounting for factors such as varying work environments, different task demands, and the presence of multiple external influences. Additionally, involving a more diverse range of test subjects in future studies would provide a more comprehensive view of the proposed work, particularly considering individuals with different demographics, such as age, gender, and physical capability. This diversity could enhance the robustness of the findings and make the framework applicable to a broader population. By expanding the research to include these real-world settings and diverse participants, we can improve the applicability of our findings and further refine the framework to better support worker safety and well-being in actual workplace contexts.

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References

Ahad, M. A. R., Ahmed, M., Das Antar, A., Makihara, Y., & Yagi, Y. (2021). Action recognition using kinematics posture feature on 3D skeleton joint locations. *Pattern Recognition Letters*, *145*, 216–224. https://doi.org/10.1016/j.patrec.2021.02.013

Soofi, A. A., & Awan, A. (2017). Classification techniques in machine learning: applications and issues. *Journal of Basic & Applied Sciences*, *13*, 459-465. https://doi.org/10.6000/1927-5129.2017.13.76

Asghari Oskoei, M., & Hu, H. (2007). Myoelectric control systems—A survey. *Biomedical Signal Processing and Control*, *2*(4), 275–294. https://doi.org/10.1016/j.bspc.2007.07.009

Baby, D., Devaraj, S. J., Hemanth, J., & Anishin Raj, M. M. (2021). Leukocyte classification based on feature selection using extra trees classifier: A transfer learning approach. *Turkish Journal of Electrical Engineering and Computer Sciences*, *29*, 2742–2757. https://doi.org/10.3906/elk-2104-183

Bukhari, W. M., Yun, C. J., Kassim, A. M., & Tokhi, M. O. (2020). Study of K-Nearest Neighbour classification performance on fatigue and non-fatigue EMG signal features. *International Journal of Advanced Computer Science & Applications*, *11*(8), 41–47. https://doi.org/10.14569/IJACSA.2020.0110806

Dellacasa Bellingegni, A., Gruppioni, E., Colazzo, G., Davalli, A., Sacchetti, R., Guglielmelli, E., & Zollo, L. (2017). NLR, MLP, SVM, and LDA: A comparative analysis on EMG data from people with trans-radial amputation. *Journal of Neuroengineering and Rehabilitation*, *14*(1), 82–82. https://doi.org/10.1186/s12984-017-0290-6

Fortini, L., Lorenzini, M., Kim, W., De Momi, E., & Ajoudani, A. (2020). A Real-time Tool for Human Ergonomics Assessment based on Joint Compressive Forces. *2020 29th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, 1164–1170. https://doi.org/10.1109/RO-MAN47096.2020.9223565

Hossain, M. S., Azam, S., Karim, A., Montaha, S., Quadir, R., De Boer, F., & Altaf-Ul-Amin, M. (2023). Ergonomic Risk Prediction for Awkward Postures from 3D Keypoints Using Deep Learning. *IEEE Access*.

Janowitz, I. L., Gillen, M., Ryan, G., Rempel, D., Trupin, L., Swig, L., Mullen, K., Rugulies, R., & Blanc, P. D. (2006). Measuring the physical demands of work in hospital settings: Design and implementation of an ergonomics assessment. *Applied Ergonomics*, *37*(5), 641–658. https://doi.org/10.1016/j.apergo.2005.08.004

Kotsiantis, S. B. (2007). Supervised machine learning: A review of classification techniques. *Informatica (Ljubljana)*, *31*(3), 249–268.

Kukreja, H., Bharath, N., Siddesh, C. S., & Kuldeep, S. (2016). An introduction to artificial neural network. *Int J Adv Res Innov Ideas Educ*, *1*, 27-30.

Kumari, S., Tewari, V. K., Kumar, S., & Sahni, R. K. (2023). An Electromyographical Approach to Evaluate the Effect of Load on Agricultural Worker during Push–Pull Operation. *Journal of Biosystems Engineering*, *48*(4), 402–411. https://doi.org/10.1007/s42853-023-00200-1

Li, K., Zhang, J., Wang, L., Zhang, M., Li, J., & Bao, S. (2020). A review of the key technologies for sEMG-based human-robot interaction systems. *Biomedical Signal Processing and Control*, *62*, 102074–. https://doi.org/10.1016/j.bspc.2020.102074

Li, Z., Yu, Y., Xia, J., Chen, X., Lu, X., & Li, Q. (2024). Data-driven ergonomic assessment of construction workers. *Automation in Construction*, *165*, 105561-. https://doi.org/10.1016/j.autcon.2024.105561

Liao, L., Liao, K., Wei, N., Ye, Y., Li, L., & Wu, Z. (2023). A holistic evaluation of ergonomics application in health, safety, and environment management research for construction workers. *Safety Science*, *165*, 106198-. https://doi.org/10.1016/j.ssci.2023.106198

Lin, P. C., Chen, Y. J., Chen, W. S., & Lee, Y. J. (2022). Automatic real-time occupational posture evaluation and select corresponding ergonomic assessments. *Scientific Reports*, *12*(1), 2139–2139. https://doi.org/10.1038/s41598-022-05812-9

Liu, Q., Liu, Y., Zhang, C., Ruan, Z., Meng, W., Cai, Y., & Ai, Q. (2021). sEMG-Based Dynamic Muscle Fatigue Classification Using SVM With Improved Whale Optimization Algorithm. *IEEE Internet of Things Journal*, *8*(23), 16835–16844. https://doi.org/10.1109/JIOT.2021.3056126

Lorenzini, M., Kim, W., De Momi, E., & Ajoudani, A. (n.d.). A Real-time Graphic Interface for the Monitoring of the Human Joint Overloadings with Application to Assistive Exoskeletons. In *Wearable Robotics: Challenges and Trends* (pp. 281–285). Springer International Publishing. https://doi.org/10.1007/978-3-030-01887-0_54

Lowe, B. D., Weir, P., & Andrews, D. (2014). Observation-based posture assessment: review of current practice and recommendations for improvement. https://stacks.cdc.gov/view/cdc/24085/cdc_24085_DS1.pdf

Middlesworth, M. (2012). A step-by-step guide rapid upper limb assessment (RULA). *Ergonomics Plus*, 13.

Nayak, G. K., & Kim, E. (2021). Development of a fully automated RULA assessment system based on computer vision. *International Journal of Industrial Ergonomics*, *86*, 103218-. https://doi.org/10.1016/j.ergon.2021.103218

Ossai, C. I., & Wickramasinghe, N. (2022). GLCM and statistical features extraction technique with Extra-Tree Classifier in Macular Oedema risk diagnosis. *Biomedical Signal Processing and Control*, *73*, 103471–. https://doi.org/10.1016/j.bspc.2021.103471

Park, J., Kim, Y., & Han, B. (2018). Work Sectors with High Risk for Work-Related Musculoskeletal Disorders in Korean Men and Women. *Safety and Health at Work*, *9*(1), 75–78. https://doi.org/10.1016/j.shaw.2017.06.005

Paul, Y., Goyal, V., & Jaswal, R. A. (2017). Comparative analysis between SVM & KNN classifier for EMG signal classification on elementary time domain features. *2017 4th International Conference on Signal Processing, Computing and Control (ISPCC)*, *2017-*, 169–175. NEW YORK: IEEE. https://doi.org/10.1109/ISPCC.2017.8269670

Phinyomark, A., Phukpattaranont, P., & Limsakul, C. (2012). Feature reduction and selection for EMG signal classification. *Expert Systems with Applications*, *39*(8), 7420–7431. https://doi.org/10.1016/j.eswa.2012.01.102

Reaz, M. B. I., Hussain, M. S., & Mohd-Yasin, F. (2006). Techniques of EMG signal analysis: Detection, processing, classification and applications. *Biological Procedures Online*, *8*(1), 11–35. https://doi.org/10.1251/bpo115

Rechy-Ramirez, E. J., & Hu, H. (2011). Stages for Developing Control Systems using EMG and EEG signals: A survey. *School of computer science and electronic engineering, University of Essex*, 1744-8050.

Reyes-Fernandez, M. C., Posada-Gomez, R., Martinez-Sibaja, A., Aguilar-Lasserre, A. A., & Flores Cuautle, J. J. A. (2024). Wrist EMG Monitoring Using Neural Networks Techniques. *Journal of Sensors*, *2024*, 1–9. https://doi.org/10.1155/2024/5526158

Roberts, D., Torres Calderon, W., Tang, S., & Golparvar-Fard, M. (2020). Vision-Based Construction Worker Activity Analysis Informed by Body Posture. *Journal of Computing in Civil Engineering*, *34*(4). https://doi.org/10.1061/(ASCE)CP.1943-5487.0000898

Rodrigues, P. B., Xiao, Y., Fukumura, Y. E., Awada, M., Aryal, A., Becerik-Gerber, B., Lucas, G., & Roll, S. C. (2022). Ergonomic assessment of office worker postures using 3D automated joint angle assessment. *Advanced Engineering Informatics*, *52*, 101596-. https://doi.org/10.1016/j.aei.2022.101596

Seo, J., & Lee, S. (2021). Automated postural ergonomic risk assessment using vision-based posture classification. *Automation in Construction*, *128*, 103725-. https://doi.org/10.1016/j.autcon.2021.103725

Sharma, D., Kumar, R., & Jain, A. (2022). Breast cancer prediction based on neural networks and extra tree classifier using feature ensemble learning. *Measurement: Sensors*, *24*, 100560–. https://doi.org/10.1016/j.measen.2022.100560

Subasi, A. (2013). Classification of EMG signals using PSO optimized SVM for diagnosis of neuromuscular disorders. *Computers in Biology and Medicine*, *43*(5), 576–586. https://doi.org/10.1016/j.compbiomed.2013.01.020

Ventura, L., Lorenzini, M., Kim, W., & Ajoudani, A. (2021). A Flexible Robotics-Inspired Computational Model of Compressive Loading on the Human Spine. *IEEE Robotics and Automation Letters*, *6*(4), 8229–8236. https://doi.org/10.1109/LRA.2021.3100936

Wang, D., Dai, F., & Ning, X. (2015). Risk Assessment of Work-Related Musculoskeletal Disorders in Construction: State-of-the-Art Review. *Journal of Construction Engineering and Management*, *141*(6). https://doi.org/10.1061/(ASCE)CO.1943-7862.0000979

Yan, X., Li, H., Li, A. R., & Zhang, H. (2017). Wearable IMU-based real-time motion warning system for construction workers' musculoskeletal disorders prevention. *Automation in Construction*, *74*, 2–11. https://doi.org/10.1016/j.autcon.2016.11.007

Yu, Y., Li, H., Umer, W., Dong, C., Yang, X., Skitmore, M., & Wong, A. Y. L. (2019a). Automatic Biomechanical Workload Estimation for Construction Workers by Computer Vision and Smart Insoles. *Journal of Computing in Civil Engineering*, *33*(3). https://doi.org/10.1061/(ASCE)CP.1943-5487.0000827

Yu, Y., Li, H., Yang, X., Kong, L., Luo, X., & Wong, A. Y. L. (2019b). An automatic and non-invasive physical fatigue assessment method for construction workers. *Automation in Construction*, *103*, 1–12. https://doi.org/10.1016/j.autcon.2019.02.020