Ergonomic training tool: a pose detection-based digitalization of ISO/TR 12295 and ISO 11228-1

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Abstract: This study presents an innovative training tool based on the digitalization of ISO/TR 12295 and ISO 11228-1 standards. It utilizes Computer Vision techniques to enhance the training of operators in lifting and carrying tasks, addressing the prevalent issue of musculoskeletal disorders (MSDs) in occupational settings caused by repetitive movements and improper techniques. The system employs pose detection and object recognition techniques, to enable real-time monitoring of operator movements. Additionally, it facilitates the semi-automated generation of reports that incorporate ergonomic indicators such as the Revised National Institute for Occupational Safety and Health (NIOSH) Lifting Equation and the Rapid Upper Limb Assessment (RULA) index. These reports serve as educational tools, helping operators understand their actions and identify potential ergonomic risks. In a case study, the system effectively identified incorrect actions and provided comprehensive reports with in-depth analyses and actionable improvement suggestions. The system demonstrated adaptability across a diverse range of individuals within the same occupational setting, thereby enhancing its practical utility. While these results are encouraging, it is important to note that the system is currently in a pilot phase and requires further validation through testing on a larger and more diverse sample in various occupational settings

Keywords: Safety; Digitalization; Artificial Intelligence; Object Detection; Ergonomics; Training 4.0

1.Introduction

Work-related musculoskeletal disorders (WMSDs) represent a significant threat to the health and safety of workers in modern workplaces (Punnett & Wegman, 2004). Incorrect posture, repetitive movements, and unsafe lifting practices frequently induce these conditions. The development of WMSDs is linked to the repetition of incorrect actions over time. Even when identified, it can be challenging for workers to break these habits and adopt new, safer practices (Rodrigues Ferreira Faisting & De Oliveira Sato, 2019). It is thus imperative to address the issue at its source and to implement a best-practice comprehensive training at the earliest possible stage. However, the conventional approach to workplace safety training, which relies on theoretical lectures and static simulations, may not be an effective means of equipping workers with the practical skills required to prevent accidents and WMSDs (Longo et al., 2023). ISO standards provide guidelines on the safe manual handling of materials, to reduce ergonomic risks. ISO/TR 12295 guides on selecting the appropriate standard for ergonomic risk assessments when operators perform lifting, carrying, pulling, or pushing operations (ISO, 2014, 2021). Nevertheless, to the best of the authors' knowledge, this ISO assessment discussed in this paper is not currently employed in the training process. In contrast, it is employed to monitor the habits of workers or to assess ergonomic risks. Previous studies have proposed to assess ergonomics risks through the ISO/TR 12295 (Carrera et al., 2020) or the Occupational Repetitive Actions (OCRA) checklist method (Occhipinti & Colombini, 2021). Others have proposed the use of wearable sensors to assess the risks associated with biomechanical overload during manual material handling, by ISO 11228 and ISO/TR 12295 (Giannini et al., 2020), or a toolkit for the analysis and prevention of WMSDs (Occhipinti & Colombini, 2016). This study innovatively-introduces a training tool based on the digitalization of the ISO/TR 12295, coupled with a Computer Vision-based system, to enhance the training of workers performing lifting and carrying tasks as standardized in ISO 11228-1. This Computer Vision system allows for real-time monitoring and feedback, offering a more engaging and precise training experience. Workers can directly observe and correct their posture and movement patterns during lifting and carrying tasks. The system also facilitates the integration of ergonomic assessment tools, such as the Revised National Institute for Occupational Safety and Health (NIOSH) Lifting Equation or the Rapid Upper Limb Assessment (RULA), into the training process(McAtamney & Nigel Corlett, 1993; Waters et al., 1993). Furthermore, the system enables the generation of bespoke feedback reports that identify potential ergonomic risks associated with specific lifting and carrying techniques employed by individual employees.

2.Background

2.1 WMSDs and Ergonomics Training

WMSDs represent a significant burden on workers, employers, and healthcare systems worldwide. These disorders comprise a range of painful conditions affecting the muscles, tendons, ligaments, joints, and nerves (Di Tecco et al., 2021). Common examples include carpal tunnel syndrome, tendonitis, and lower back pain. WMSDs are not caused by single, dramatic events, but rather develop over time due to repetitive motions, awkward postures, forceful exertions, and vibrations WMSDs are prevalent across various occupations, making them one of the most common work-related health problems (Di Tecco et al., 2021). The impact of WMSDs is considerable, resulting in pain, discomfort, and limitations in job performance for affected workers. This can lead to increased absenteeism, reduced productivity, and higher healthcare costs (Yang et al., 2023). Ergonomic Training (ET) is a preventive measure to reduce WMSDs. The objective of ET is to educate workers about potential risks through lectures and/or on-the-job training, to improve workers' health (Bos et al., 2006; Dalkilinç & Kayihan, 2014). However, it is important to note that the effectiveness of this training may be limited. While many companies implement this type of training to comply with regulatory recommendations, its efficacy is not guaranteed (Rodrigues Ferreira Faisting & De Oliveira Sato, 2019). Furthermore, conventional training methods frequently lack the dynamic and personalized approach required to effectively address the individual needs of worker and the specific demands of their job roles (Longo et al., 2023). The implementation of a personalized ergonomic training programme and the provision of detailed feedback reports containing actionable improvement suggestions are essential strategies to reduce the incidence of WMSDs among workers.

2.2 ISO/TR 12295, ISO 11228-1 and Ergonomics Indexes

ISO/TR 12295 is a technical report that offers guidance on implementing the ISO 11228 series and/or ISO 11226. It specifically focuses on ergonomics and manual handling, providing illustrative examples, flowcharts, and decision-making tools to simplify the risk assessment process. The report also proposes the implementation of workstation design, appropriate handling techniques, and training programs to promote safe manual handling practices (ISO, 2014). As per ISO/TR 12295, the risk assessment starts with a quick evaluation to determine the presence or absence of acceptable or critical hazards in lifting, carrying, pulling, or pushing operations. Subsequently, ISO/TR 12295 directs the assessment towards the relevant ISO standard, contingent upon the identified risk. This study will focus on the standardized lifting and carrying risk assessment outlined in ISO 11228-1 (ISO, 2021). It specifies the recommended limits for lifting, lowering, and manual handling of an object weighing 3 kilograms or more, taking into account the intensity, frequency, and duration of the activity. Also, it employs the Revised NIOSH Lifting Equation as a lifting index to assess potential hazards during lifting and carrying actions. The Revised NIOSH Lifting Equation (Waters et al., 1993) is an ergonomic index that enables the estimation of the exposure to the risk, evaluating various factors. NIOSH developed this tool to evaluate the risk of injury associated with manual lifting tasks. The tool calculates the Recommended Weight Limit (RWL), which is the maximum weight that most healthy workers can lift safely under specific conditions during an eight-hour workday without an increased risk of developing WMSDs. Another important tool for ergonomic evaluation is the RULA index (McAtamney & Nigel Corlett, 1993), a risk assessment tool used to evaluate the risk of repetitive motion injuries in the neck, shoulders, and arms caused by work activities. It evaluates upper limb movements and postures using pivotal points such as shoulders, elbows, neck, wrists, trunk, and position of the feet, assigning scores based on the angles between body parts.

2.3 Visual systems and data acquisition methods

Vision systems play a pivotal role in enhancing the assessment of risks associated with manual material handling by offering real-time evaluations. They were widely used for ET and they contribute to the assessment of worker risk by enabling real-time monitoring of workers' activities (Jae-Hyuk et al., 2024), posture (MassirisFernández et al., 2020), and the use of personal protective equipment (Massiris et al., 2021). To date, existing research has not fully aligned with the ISO standards that govern ergonomic assessments for manual handling tasks. This study aims to address this gap by introducing a prototype tool that adheres to ISO/TR 12295 and ISO 11228-1, designed to assist experts in training workers for these tasks. Furthermore, by integrating the RULA index analysis and the revised NIOSH Lifting Equation, the tool provides comprehensive real-time feedback during training sessions, along with a detailed risk assessment report. This approach aims to enhance both the safety and performance of workers. To ensure the accuracy of a visual system for ergonomic risk assessment, the correct data must be acquired precisely. Three main categories of data acquisition methods have been developed over the years: auto-relations, observational methods, and direct/instrument-based methods (David, 2005). Auto-relations from workers can be employed to gather data on workplace exposure to physical and psychosocial factors, through worker diaries or questionnaires. Observational methods are simpler techniques for the systematic recording of workplace exposure and advanced techniques for the assessment of postural variation during dynamic activities, which may involve the use of videotaping or computer analysis.. In direct measurement, monitoring instruments with sensors attached directly to the worker measure exposure variables. Table 1 shows the application of these methods in industrial contexts. In this scenario, smart technologies are important for acquiring data through simple and advanced observational as well as direct measurements (Chan et al., 2022). Specifically, great emphasis has been placed on methods utilizing technologies such as Computer Vision (Ciccarelli et al., 2023) and Virtual Reality (Dias Barkokebas & Li, 2023) which enable effective and precise data collection and analysis. Other applications include smart wearable sensors (Donisi et al., 2021; Giannini et al., 2020), and exoskeletons (Zelik et al., 2022), which require a more invasive presence on the body of workers, giving rise to new limitations and risks for the operators (Costantino et al., 2021). In the field of data acquisition, the introduction of smart technologies is an important asset. Particularly noteworthy is the emphasis placed on advanced observational and direct methods, facilitated by technologies such as computer vision and virtual reality. These enable the collection and analysis of data with remarkable efficacy and precision (Chan et al., 2022).

Table 1: Examples of data acquisition methods

Data acquisition method	Technology	Application context	Reference
Auto-relation	Self-report questionnaire	Material Handling	(Dane et al., 2002)
Simple Observational	Video recording	Material Handling	(Fransson-Hall et al., 1995)
Advanced Observational	Computer Vision	Manufacturing	(Ciccarelli et al., 2023)
Advanced Observational	Virtual Reality	Training	(Dias Barkokebas & Li, 2023)
Direct	Exoskeleton	Material Handling	(Zelik et al., 2022)
Direct	Wearable Inertial Sensor	Material Handling	(Donisi et al., 2021)

3. Tool design and technical functionalities

This section presents the design and the technical functionalities of the tool developed. The steps involved in building the tool, starting with the digitalization process of ISO/TR 12295 and ISO 11228-1, and continuing with the data acquisition method based on Computer Vision are presented. Before delving into how the tool works, a brief introduction to the operation of ISO/TR 12995 and ISO 11228-1 is necessary.

3.1 ISO/TR 12295 and ISO 11228-1 analysis

As previously stated, ISO/TR 12295 guides users in selecting the appropriate ISO standard for risk assessment and it is divided into two levels. The decision-making process outlined in ISO/TR 12295 commences at the first level with pivotal questions that assess the relevance of the job's basic conditions in relation to specific standards. Subsequently, the user is guided to the appropriate quick assessment, which constitutes the second level. The quick assessment is designed to determine the presence or absence of acceptable or critical risks during the job. Finally, the user is redirected to the relevant ISO based on the identified risk. This study focuses on ISO 11228-1, which addresses the issue of lifting and carrying actions. To evaluate the user's job and assess the risk associated with lifting and carrying objects weighing 3 kilograms or more, five steps are necessary.

The first step involves calculating the reference mass (m_{ref}) based on the user's characteristics. The maximum weight a user can lift or carry is determined by gender and age, which are collected at the outset of the assessment process. In the second step, ISO 11228-1 instructs the user to conduct a rapid assessment by answering pivotal questions. This step aims to establish whether the user can lift or carry objects weighing 3 kg or more without experiencing acceptable or critical conditions. The initial evaluation determines whether the job necessitates further analysis due to unacceptable conditions, critical conditions requiring adaptation, or non-critical risks requiring further analysis. In addition, this step examines other factors related to the work environment and object characteristics to determine their importance. If the risk is not critical, Step 3 RWL for the job, considering working posture, object position, lifting frequency, and position. Also, a Lifting Index (LI) is calculated to assess the level of risk. using the Revised NIOSH Lifting Equation. It determines the RWL by means of equation 1 where LC is the maximum recommended weight, HM is the horizontal distance multiplier, VM is the vertical position multiplier, DM is the vertical displacement multiplier, FM is the frequency multiplier, CM is the object grip quality multiplier and AM is the asymmetry multiplier.

$$RWL = LC \times HM \times VM \times DM \times FM \times CM \times AM \quad (1)$$

Given the lifted effective mass, the LI is calculated as follows:

$$LI = \frac{m_A}{RWL} \qquad (2)$$

If the LI is greater than 1, there is a current risk and ISO will suggest necessary actions. The risk assessment proceeds to step 4 and step 5, where the cumulative mass (m_{cum}) is calculated by multiplying the mass per carrying frequency. In the final two steps of the procedure, the reference mass is calculated by multiplying the carried mass per carrying frequency and compared to a specified limit. This comparison determines whether the carrying task is acceptable.

3.2 Tool design considerations

The proposed risk assessment tool employs an advanced observational method that leverages the Computer Vision technique with a single 16-megapixel wide-angle camera oriented perpendicular to the sagittal plane. It was developed in Python and utilizes the holistic module of the Mediapipe library to identify workers during material handling tasks. Mediapipe is an open-source framework (*MediaPipe*, 2024) that provides pre-built machine-learning pipelines for various tasks, including facial recognition and pose estimation. The holistic module (*Holistic Landmarks Detection Task Guide MediaPipe*, 2024) focuses on real-time multi-landmark tracking of the human body, providing data points for key body features (Figure 1). Moreover, an object detection model was trained on a bespoke dataset comprising 5000 box images sourced from Roboflow (*Box Roboflow Universe Search*, 2024), a platform for computer vision datasets and models. The object detection model, which is likely constructed using Yolo v9 Ultralytics (Ultralytics, 2024), a prevalent deep-learning framework for object detection, facilitates the identification and potential tracking of boxes within the worker's environment. The integration of these functionalities enables the tool to analyse the behaviour and interactions of workers with boxes during material handling tasks.

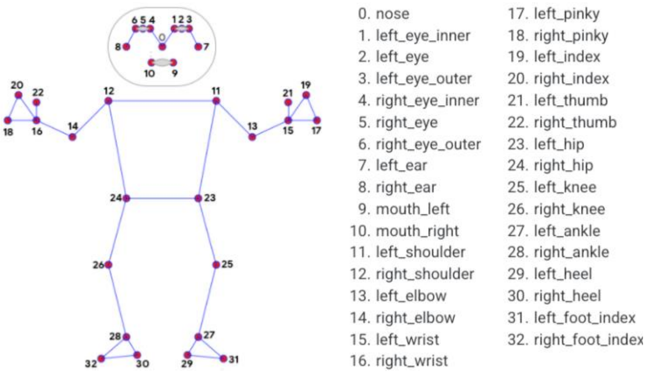

Figure 1: Mediapipe body landmarks

3.3 Functioning of the Tool

Figure 2 illustrates the three phases of the risk assessment framework.

Phase 1: One-to-one training with expert guidance on ISO/TR 12295 implementation

In the first phase, an expert provides a comprehensive explanation of the tasks of the process to the trainees. Subsequently, the tool collects preliminary information in accordance with the ISO/TR 12295 by posing specific questions in terms of age, gender, and height. Environmental aspects are assumed to be non-critical.

Phase 2: On-the-job training and application of the ISO 11228-1

The on-the-job training starts in the second phase. The tool collects the operator's landmarks, and the distance covered by the operator during the carrying and detects the box to identify the actions. The action identification process consists of two steps to ensure a more precise assessment of the worker's tasks. Initially, the system detects the operator's pose based on the coordinates of their landmarks and their position in relation to the box. Three poses can be identified when the operator holds the box:

- Lifting, when a greater angle of 35° is created between the wrist, elbow, and shoulder, and the y-coordinates of the hands are located between the shoulders and abdomen;
- Overhead Lifting, when the wrist is above the coordinate of the eyes;
- Power Lifting, when the y-coordinate of the eyes is lowered below the line fixed at the height of the hips. The sequence of these poses is saved in a data frame along with their duration.

Four different types of action categories are then defined by the aggregation of sequential poses: Lowering, Floor Lowering, Upper Lifting, and Upper Floor Lifting. Lowering refers to the transition from Overhead Lifting to Lifting, Floor Lowering refers to the transition from Lifting to Power Lifting, Upper Lifting refers to the transition from Lifting to Overhead Lifting, and Upper Floor Lifting refers to the transition from Power Lifting to Lifting.

The distance the operator covers while transporting the box is also recorded, based on the difference between the x-coordinate of the worker's nose. The frequency of carrying is also recorded. All the data collected by the tool is used to conduct the ISO 11228-1 quick assessment. If the risk is deemed acceptable, the process automatically advances to phase 3. However, if the risk is not acceptable, the tool evaluates for critical conditions. If no critical conditions are detected, the system calculates the LI for each action as well as the cumulative mass evaluation. In the event of critical conditions, the system halts further evaluations and immediately issues an alert to prompt necessary adaptations to the activities. The Lifting Index is then calculated using the NIOSH equation, with two LIs calculated for each action, one for the initial position (LI1) and one for the final position (LI2). The mean LI is employed solely for evaluation purposes. The factors that contribute to the calculation of the RWL result from the variation of the coordinates of the landmarks. Only AM and CM are set equal to 1 due to the limitation of a single camera and the impossibility of calculating them. The final step of phase 2 is the Cumulative Mass Check. This evaluates the safety of lifting conditions based on cumulative mass and transport distance. Moreover, it defines recommended thresholds for different durations and distances, after which it determines whether the provided mass is acceptable. The RULA index is not mentioned in the ISO 11228-1 however its analysis has been considered to provide a more comprehensive analysis of operators' posture behaviour. The RULA index evaluates the operator's posture by considering the x and y coordinates of the shoulder, elbow, wrist, nose, hip, pinkie, and ankle landmarks. However, due to the limitations of the vision provided by the single camera, some items related to specific body parts cannot be considered. The movement of the wrists and the movement of the elbows on the transverse plane are not considered. Nevertheless, it is worth noting that for the carrying and lifting tasks of this study, a significant asymmetry of the wrist and the elbows is quite rare. In such a situation, it is assumed that there is an absence of asymmetry and that the lower score is assigned to these two elements in calculating the RULA index.

Phase 3: Expert analysis and training outcome evaluation

Once the material handling job has been completed, the third phase starts. An expert analyses the reports generated by the tool using the RULA index and LI trends. These trends provide insights into potential ergonomic risks associated with lifting postures. The report highlights instances where the worker utilized correct lifting techniques and identifies areas where movements could be improved to minimize strain. Finally, the expert evaluates the results and decides whether the operator must repeat the job or if the training is finished.

4. Experiment and results

To assess the efficacy of the computer vision tool in identifying ergonomic hazards, a controlled experiment was conducted which simulated a training session for warehouse workers. Two participants performed a series of material handling tasks that involved lifting and carrying a box. The box was moved by the participant across a variety of shelves, representing the diverse range of lifting and carrying scenarios encountered in real-world warehouses.

This experimental setup enabled the tool to analyse the participant's lifting techniques and postures in a controlled environment, providing valuable data for assessing its ability to detect potential ergonomic risks. Table 2 reports the experiment details.

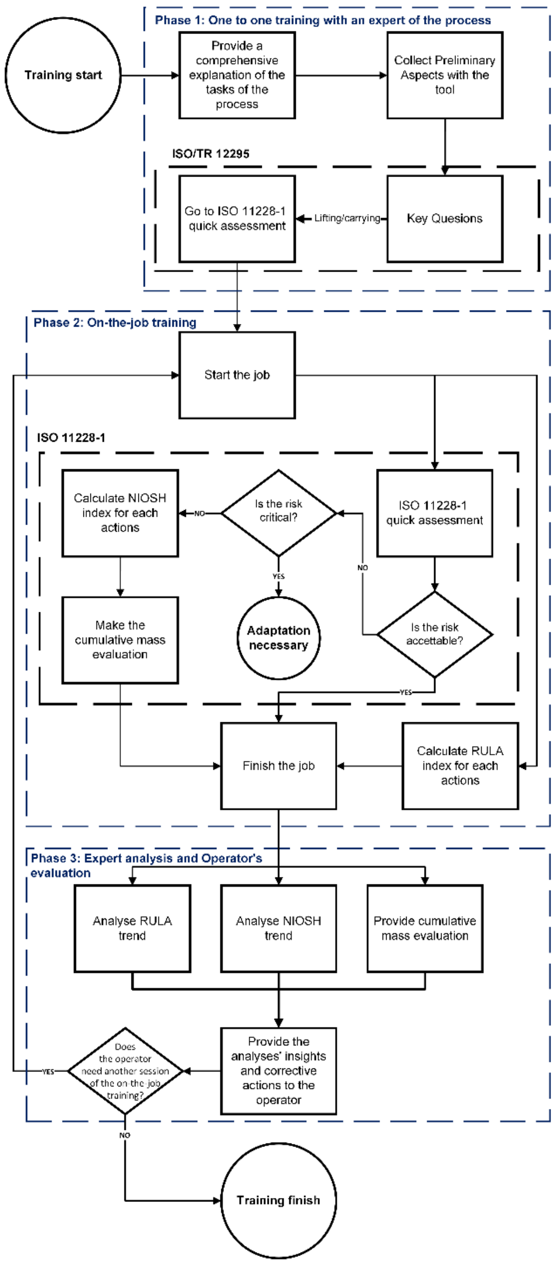

Figure 2: Risk Assessment Tool framework

Table 2: Experiment details

	Participant 1	Participant 2
Age	25	24
Gender	Male	Male
Height	185 cm	182 cm
Mass of the box	12 kg	11 kg
m_{ref}	25 kg	25 kg

One of the authors also participated in the experiment as an expert in the process. In both cases, the quick assessment identified conditions that were not acceptable but not critical, thus allowing LI and cumulative mass analysis. The tool calculated the LI and RULA index for each action, as well as the cumulative mass evaluation. Figure 3 shows the trend of the LI for participant 1 and participant 2. This result demonstrates that while mass may appear to be the primary factor in the NIOSH assessment, measurements and their multipliers can significantly impact the analysis of an activity.

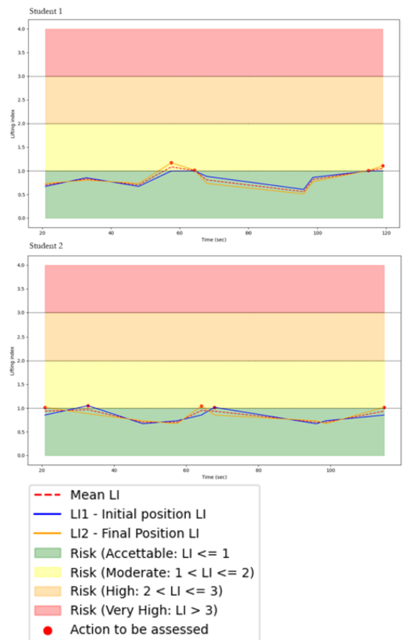

Figure 3: LI trend of participant 1 and participant 2

In particular, the most common risky action related to a higher LI is the improper lifting of a load that is too heavy for the height of the shelf. In such cases, it is essential to either reduce the mass or use a support to facilitate the operation. Another type of action that has been evaluated as risky is the lowering. In this case, as will be seen in the analysis of the RULA index, the participants failed to correctly stop the lowering motion, which could result in a potential hazard. Although the value of the cumulative mass differs between the two participants, the acceptability conditions remain unchanged. It is necessary to reduce the transported load as the weight associated with the transport frequency exceeds the recommended threshold in one minute. The RULA report is generated, identifying all actions with an index equal to or greater than 3. A comparison is made between the optimal way to act and the action that was performed (Figure 4). Finally, the expert provided specific recommendations to the participants, without requiring them to repeat the task.

4. Conclusion and future work

The principal objective of this study was to assess the efficacy of an innovative training tool in reducing the likelihood of WMSDs, resulting from incorrect lifting and carrying techniques. This was achieved by developing a digitized version of the ISO/TR 12295 and ISO 11228-1 standards. The trial demonstrated the potential of this computer vision tool to identify ergonomic risks in material handling tasks. The tool can analyse worker posture and box interaction using the RULA index and LI, calculated by the NIOSH equation. It then provides targeted improvement suggestions to enable workers to adopt safer lifting techniques during their training.

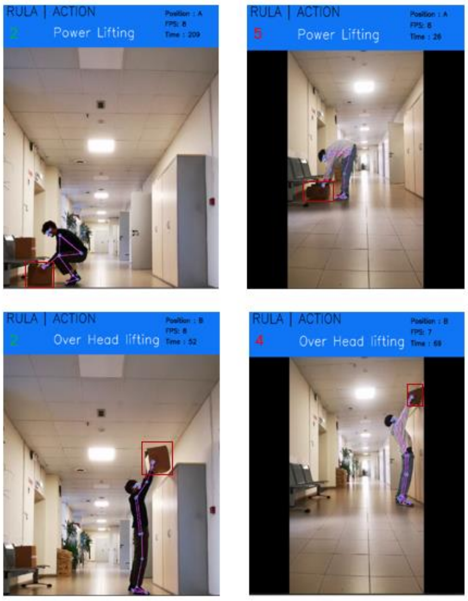

Figure 4: RULA comparison between actions

Furthermore, this framework can be seamlessly integrated with the conventional training system, where the company must provide theoretical training sessions, represented in the first phase of the framework. The conducted experiment also confirms its potential. Bad posture and incorrect actions have been identified, and comprehensive suggestions have been provided to the operators with the help of an expert.

However, the study presents limitations related to the experimental settings. The study was conducted in a simulated environment, which may not fully reflect the complexities of a real-world scenario. The framework is restricted to one participant and one lifted/carried object, meaning that the presence of multiple individuals or different objects may affect the tool analysis. It is crucial to consider the influence of pulling and pushing actions during the analysis, as these can significantly impact outcomes. Additionally, utilising a single camera limits the scope to assess all operator actions, such as wrist and elbow movements.

Future studies will extend the framework to encompass the remaining standards of the ISO/TR 12295, namely ISO 11228-2, ISO 11228-3, and ISO 11226, enhancing its ability to provide a more comprehensive assessment of ergonomic risks in different workplace scenarios. To achieve optimal performance, the tool should be integrated with additional cameras and sensors to capture a more detailed picture of worker movements. It is also recommended that different object detection models be employed to recognize a wider range of material handling tasks. Finally, the main challenge lies in testing the framework in real industrial environments, which are characterized by numerous interference factors.

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