Joint CSCE Construction Specialty & CRC Conference 2025
Conférence conjointe spécialisée en construction de la SCGC et CRC-2025

Montreal, Quebec
July 28-31, 2025 / *28-31 juillet 2025*

ERGONOMIC RISK ASSESSMENT IN MANUAL CONSTRUCTION DEMOLITION USING POSE ESTIMATION AND REBA ANALYSIS

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ABSTRACT

Manual construction demolition involves repetitive, physically demanding tasks that expose workers to significant ergonomic risks, including musculoskeletal disorders (MSDs). This study integrates computer vision-based pose estimation with the Rapid Entire Body Assessment (REBA) framework to evaluate these risks systematically. Using the YOLOv8 pose estimation model, key joint angles such as neck, shoulder, and lower body movements were analyzed from video footage of manual demolition tasks. Custom algorithms quantified postural deviations, categorized into low, medium, and high-risk levels based on REBA criteria. The system produced real-time visual overlays, highlighting key ergonomic risks and enabling immediate and post-task analysis. Validation against manually annotated ground truth data demonstrated the system's reliability and precision in identifying hazardous postures, particularly during tasks like repetitive bending, awkward lifting, and hammering. Preliminary findings highlight the most critical postures and movements contributing to high ergonomic risk, emphasizing the need for improved intervention strategies to enhance worker safety. This study highlights the potential of computer vision tools and key joint angle estimation in improving worker safety through scalable, automated ergonomic evaluations tailored to construction demolition environments. By integrating automated YOLOv8 pose estimation with ergonomic evaluation frameworks, this research advances the precision of risk identification and offers actionable insights for reducing injuries in manual construction demolition.

1. INTRODUCTION

Manual construction demolition is among the most physically demanding tasks in the construction industry, exposing workers to high ergonomic risks due to repetitive movements, awkward postures, and heavy lifting (Sousa et al. 2014). These physically intensive activities place substantial strain on workers' musculoskeletal systems, often leading to injuries that can have long-term health implications. Consequently, these occupational hazards contribute significantly to musculoskeletal disorders (MSDs), which remain a leading cause of workplace injuries worldwide (Da Costa and Vieira 2010). Effective ergonomic assessments are crucial to mitigating these risks. The traditional methods, such as on-site observations and self-reported surveys, are often criticized for being subjective, inconsistent, and labor-intensive (Chiasson et al. 2012). These limitations underscore the need for innovative approaches to ergonomic evaluation that are both accurate and scalable.

Advances in computer vision technologies offer new opportunities for automating ergonomic risk assessments through pose estimation techniques. Pose estimation algorithms can detect and track key body joints from video data, enabling real-time posture evaluation without requiring specialized sensors or wearable devices (Cao et al. 2021; Kim et al. 2021; MassirisFernández et al. 2020). By eliminating the dependence on manual observation, these algorithms improve the objectivity and efficiency of ergonomic assessments. However, deploying pose estimation in dynamic and cluttered construction environments poses challenges, such as frequent worker movement, risk level assessments, variable lighting conditions, and complex backgrounds (Yu et al. 2019). Overcoming these obstacles is essential to ensure the reliable application of computer vision in real-world settings.

To address these challenges, this study integrates pose estimation with the Rapid Entire Body Assessment (REBA). REBA is a widely accepted ergonomic evaluation framework for assessing whole-body postures based on key joint angles (Hignett and Mcatamney 2000). By assigning ergonomic risk levels, REBA provides actionable insights for identifying hazardous postures that require corrective interventions. Automating REBA risk levels through pose estimation enhances the consistency and scalability of ergonomic assessments, particularly in dynamic construction settings.

This paper introduces a methodology that combines pose estimation with REBA to evaluate ergonomic risks in manual construction demolition tasks. By leveraging YOLOv8 pose estimation output to quantify body movements and calculate REBA risk levels automatically, the proposed system enables continuous ergonomic monitoring. This approach demonstrates the potential for integrating computer vision-based techniques into construction site safety protocols, paving the way for real-time risk assessment and more effective injury prevention strategies in manual construction demolition tasks.

2. LITERATURE REVIEW

Manual construction demolition is inherently physically demanding, exposing workers to significant ergonomic hazards due to repetitive tasks, awkward postures, and forceful exertions. Numerous studies linked these factors to a high incidence of musculoskeletal disorders (MSDs) among construction laborers, emphasizing the importance of continuous ergonomic monitoring (Kwon et al. 2022; Menanno et al. 2024). Traditional ergonomic assessment methods, including observational checklists and manual evaluations, were extensively applied but are often criticized for being time-intensive, subjective, and prone to human error (De Freitas et al. 2019).

The emergence of computer vision technologies has facilitated the use of pose estimation techniques in ergonomics research. Using pose estimation model enabled automated tracking of human body by extracting skeletal key points from video footage, enhances accuracy and reduces observer bias (Kim et al. 2021; MassirisFernández et al. 2020). These methods provided a scalable, data-driven alternative to manual posture assessment, particularly useful in dynamic environments like construction sites where manual evaluation may be limited due to environmental complexities (Yu et al. 2019).

REBA is a validated tool for evaluating ergonomic risks by analyzing body postures, joint angles, and limb positioning. It assigned risk scores based on posture severity, highlighting tasks requiring immediate corrective actions (Menanno et al. 2024). Combining pose estimation output with the REBA risk levels system can automate ergonomic evaluations, offering more consistent and objective risk assessments. Recent research demonstrated that 3D poses estimation methods using depth sensors and advanced neural networks significantly improved the accuracy of risk assessment (Paudel et al. 2022).

Given the physical demands of construction demolition, real-time ergonomic monitoring is crucial. While pose estimation has been employed separately in various work environments, limited research has explored their combined application in demolition contexts. This highlighted an opportunity for further investigation into integrating these technologies to improve occupational safety by enabling continuous ergonomic monitoring and intervention (Fan et al. 2024). Incorporating specialized datasets tailored to construction activities enhanced the system's accuracy and reliability (De Freitas et al. 2019).

Despite advancements in ergonomic risk assessment, a significant gap persists in literature. Although various studies have utilized pose estimation techniques independently, their integration remains underexplored in automated REBA risk levels assessment for key joint angel computation, particularly in dynamic and high-risk environments such as manual construction demolition. This lack of research validating their combined application underscores a critical opportunity to enhance real-time risk level assessment and develop more effective intervention strategies.

3. METHODOLOGY

The methodology for this study consists of a computer vision-based pose estimation framework to assess ergonomic risks associated with manual construction demolition tasks. The proposed system combines the YOLOv8 pose estimation model with custom-built algorithms for calculating joint angles and classifying ergonomic risk levels based on established criteria. The process follows four key steps: Data Collection, Key Joint Detection, Angle Computation, and Risk Categorization.

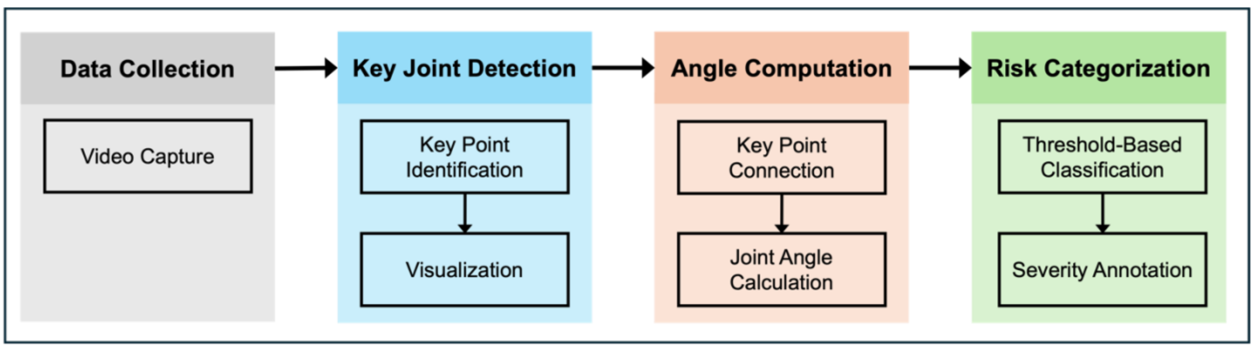


Figure 1. Workflow of the ergonomic risk assessment methodology

Figure 1 illustrates the workflow of the ergonomic risk assessment methodology, progressing through data collection, key joint detection, angle computation, and risk categorization to identify and evaluate ergonomic risks in manual construction demolition tasks.

3.1. Data Collection: The initial step focuses on capturing high-quality video footage of various manual construction demolition tasks. This footage includes various activities typically encountered in such environments, such as bending-over tasks, hammering, and lifting. The recordings are obtained from real-world construction sites to ensure the data reflects authentic working conditions, including varying lighting, cluttered backgrounds, and student movements. These scenarios provide a comprehensive foundation for assessing ergonomic risks in dynamic and challenging environments. Participants provided written informed consent before participating in the study, which was approved by the University of Hawaii at Manoa Institutional Review Board (IRB) under protocol number 2024-077.

3.2. Key Joint Detection: The recorded video frames are processed using the pre-trained YOLOv8 pose estimation model, which identifies 14 anatomical key points, including major joints such as the shoulders, elbows, hips, knees, and ankles. These key points are crucial for ergonomic evaluation. The YOLOv8 pose estimation model extracts the key points from each frame with high accuracy (Jocher et al. 2023). The detected key points are systematically validated to ensure they remain within the boundaries of the video frame. This validation process is essential for maintaining data integrity, as key points that fall outside the frame may lead to inaccurate joint angle calculations and misclassification of ergonomic risks. By filtering out erroneous detections and ensuring that only valid key points are considered, this step enhances the reliability of angle computation, improving the overall accuracy of the posture analysis.

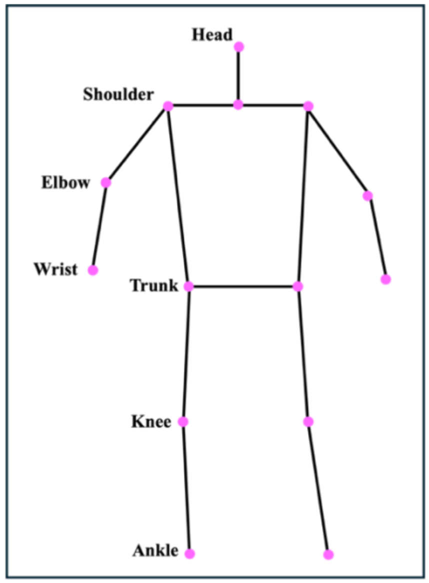


Figure 2. YOLOv8 pose estimation 14 key points detection

Figure 2 illustrates the 14 key points detected using YOLOv8 pose estimation. These detected points serve as a basis for angle estimation in the angle computational step.

3.3. Angle Computation: This step involves angle computation, where relevant joint angles are calculated using various custom functions for each joint. The computation angle function determines the angle formed by three key points representing two connecting body segments. In contrast, another unique function calculates a vector's angular deviation from the vertical axis for neck posture assessment. Additionally, the computational midpoint function identifies the midpoint between two points of shoulders, aiding in neck angle calculations, and the computational trunk angle function measures the trunk bending angle using shoulder, hip, and knee key points.

3.4. Risk Categorization: In this step, the ergonomic risk categorization step classifies calculated angles into risk levels based on established ergonomic standards from the REBA and related ergonomic assessment tools. Neck, elbow, knee, and trunk bending angles are assessed against specific thresholds to determine their severity levels. After completing the categorization, the processed video frames are enhanced with overlaid visualizations, including detected key points, skeletal connections, and computed ergonomic risk levels, enabling monitoring and the creation of an annotated video file for detailed post-task ergonomic risk level analysis for manual construction demolition tasks.

4. CASE STUDY

This case study evaluates the application of a computer vision-based pose estimation system for ergonomic risk assessment in three manual construction demolition tasks. Video recordings captured authentic working conditions, such as varying lifting and student movements, to reflect real-world scenarios. Using the YOLOv8 pre-trained model, the system identified key anatomical points, computed joint angles, and categorized ergonomic risks into low, medium, or high levels based on REBA thresholds.

4.1. Data Collection and Key Joint Detection: This step utilized three distinct video recordings, each capturing a specific manual demolition task to ensure diverse and representative data for ergonomic risk assessment. The first video focused on bending-over tasks, showcasing repetitive bending and hammering actions. The second video recorded a manual tool operation for demolition with hammering, highlighting tasks that require significant trunk bending and force application. The third video captured an impact-driven demolition task involving frequent trunk flexion and knee bending to lift and operate heavy tools. These videos were recorded in real-world demolition environments to reflect authentic working conditions, including varying lighting, background clutter, and student movements. This step focuses on detecting and tracking the movements of a single student positioned at the center of the frame.

In the key joint detection step, the YOLOv8 pre-trained pose estimation model was utilized to identify 14 critical anatomical key points on students' bodies. Detected key points were overlaid on the video frames for visual inspection. Each key point was marked with a colored circle, and skeletal connections between them were drawn to illustrate the posture of the student. These visualizations allow for clear identification of body postures and joint alignments, aiding in ergonomic risk level assessment.

4.2. Angle Computational on Key Joints: In this step, the angle between three connected key points were identified. For instance, the shoulder, elbow, and wrist were computed using vector mathematics for the elbow angle computation. First, vectors were formed between the middle joint and the two adjacent joints. Then, the dot product and magnitudes of these vectors were used to compute the cosine of the angle, which was converted to degrees using the arccosine function. This method ensures accurate angle measurements even under varying postures to calculate the angle for trunks, knees, and elbows.

The trunk bending angle was specifically calculated using the points for the shoulder, hip, and knee. Two vectors were formed: one between the shoulder and hip and the other between the hip and knee. The relative angle between these vectors determined the degree of trunk flexion. This angle provides critical insights into ergonomic risks associated with forward bending postures. Joint angles for the knees and elbows were computed by analyzing the spatial relationships between key anatomical points representing the upper and lower segments of each limb. For elbow angle computation, vectors were formed between the shoulder, elbow, and wrist. The angle between these vectors indicates the degree of elbow flexion or extension, helping to assess strain caused by repetitive bending, such as during hammering or lifting tasks. Similarly, for knee angle computation, vectors were constructed using the hip, knee, and ankle. The angle between these vectors determines the extent of knee flexion, which is crucial for evaluating ergonomic risks in tasks involving squatting, kneeling, or prolonged standing. By analyzing these joint angles, the system can identify postures that contribute to muscle fatigue, strain, or long-term musculoskeletal disorders in manual construction demolition tasks.

For neck posture evaluation, a vector was created from the midpoint between the shoulders to the nose and adjusted the angle from the nose to be at the center of the head. The angle of this vector relative to a vertical reference was computed to determine the degree of neck flexion. This is particularly useful angle in identifying risk levels for head-tilt postures.

4.3 Risk Categorization: The final step in the ergonomic assessment process is the categorization of computed joint angles into ergonomic risk levels. The risk categorization presented in Table 1 is based on ergonomic principles and adapted for this study's methodology while drawing from REBA evaluation frameworks. The table classifies risk levels into low, medium, and high based on angle deviations from a neutral posture, providing a structured approach to assessing ergonomic risks. However, it is important to note that this categorization does not fully align with the REBA method, which considers additional factors such as backward tilt in neck posture. This adaptation offers a simplified classification system suited for this study while maintaining relevance to established ergonomic assessment approaches.

Table 1. Risk categorization based on angle variations for each body part

	Low Risk	**Medium Risk**	**High Risk**
Neck	0 - 20	20 - 60	> 60
Elbow	0 - 60	60 - 90	> 90
Trunk	0 - 20	20 - 60	> 60
Knee	0 - 30	30 - 60	> 60

Low risk indicates minimal ergonomic strain and a posture close to a neutral or ergonomic standard. Medium risk represents moderate strain that may require corrective actions over prolonged durations. High risk highlights postures that pose significant ergonomic hazards and require immediate intervention.

Figures 3, 4, and 5 illustrate the ergonomic analysis of a student performing three distinct manual demolition tasks for experiencing with real tools in construction demolition tasks: bending-over task, manual tool operation with hammering, and impact-driven demolition. The postures were selected at the authors' discretion for demonstration purposes in this exploratory study. Each figure highlights critical body joint angles, detected using the YOLOv8 pose estimation model, and their corresponding ergonomic risk levels based on REBA thresholds.

Figure 3. Bending-over task

Figure 3 shows a student engaged in a manual construction task captured and analyzed using YOLOv8 pose estimation. Detected key points such as neck, shoulders, elbows, knees, and trunks, are overlaid on the student's body to highlight the posture during the activity. The angles computed for key joints, displayed in the top-left corner, provide insights into the ergonomic risks associated with the observed posture. Specifically, the student's neck and trunk angles indicate a high ergonomic risk level, suggesting potential strain due to improper posture during the task. Trunk bending angles frequently reached critical levels, emphasizing the need for corrective measures such as adjusting lifting techniques and incorporating task rotation. This analysis helps identify hazardous movements that may lead to musculoskeletal disorders, emphasizing the need for corrective measures to improve safety.

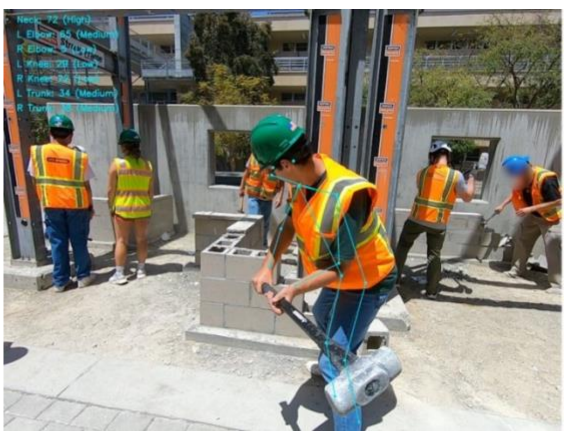


Figure 4. Manual tool operation for demolition with hammering task

Figure 4 highlights critical body joint angles and their corresponding ergonomic risk levels for the manual hammering task. The student exhibits a high-risk neck posture, likely due to the excessive downward tilt of the head while focusing on the task. This posture increases the strain on the neck muscles and could lead to discomfort or long-term musculoskeletal issues if sustained. Additionally, the left elbow and trunk postures (both left and right sides) are categorized as medium risk. The left elbow shows significant flexion, likely due to the gripping and positioning of the tool, which could result in strain or fatigue in the arm over time. However, the system incorrectly identifies the right elbow posture, due to occlusions in the scene. The trunk angles indicate moderate bending, reflecting the student's forward-leaning posture required for this task. Although categorized as medium risk, repeated or prolonged exposure to such postures can contribute to lower back strain and cumulative injuries.

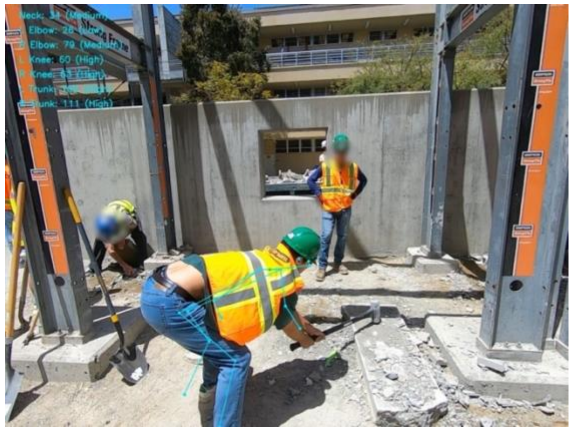


Figure 5. Impact-driven task for manual demolition

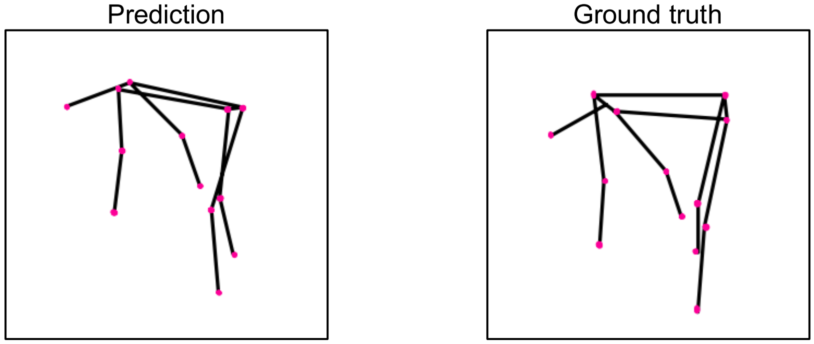
Figure 5 illustrates the ergonomic analysis of a student engaged in an impact-driven demolition task using pose estimation techniques. The system identifies critical postures, with the trunk posture being classified as a high risk, indicating significant forward bending. This posture places substantial strain on the lower back and increases the risk of musculoskeletal injuries, especially if maintained for extended periods. Additionally, the student's neck posture is also in the medium-risk category, likely due to the downward tilt. This posture exacerbates the strain on cervical muscles and could lead to discomfort or injury over time. The right elbow posture is categorized as medium risk, reflecting moderate flexion required to hold and operate the tool. Repeated actions in this position may lead to fatigue in the arm and shoulder. However, the left elbow was incorrectly detected, resulting in an incorrect location of the left elbow, which highlights an error in the system's detection of this joint due to occlusion.

These three case studies demonstrated the effectiveness of the proposed system in tracking body joints, calculating joint angles, and assessing ergonomic risks. By integrating pose estimation and REBA risk levels, the system successfully identified hazardous postures, supporting the need for proactive interventions in high-risk manual construction demolition tasks.

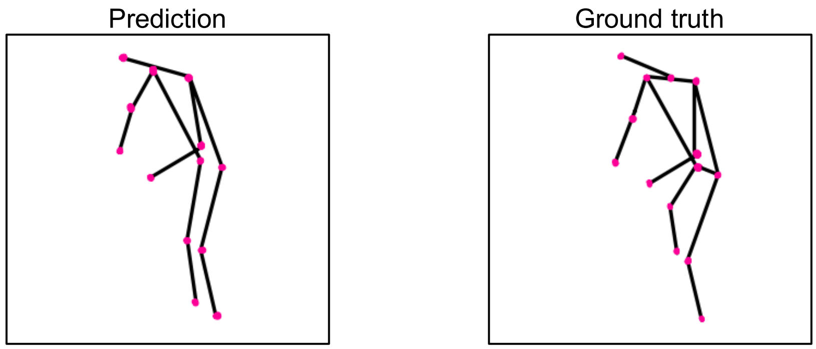
5. RESULTS

The ergonomic risk assessment system, combining pre-trained YOLOv8 pose estimation with REBA risk level assessment, was validated against ground truth annotations derived from manual assessments. The results are summarized below for three distinct demolition tasks including bending-over task, manual tool operation for demolition with hammering, and impact-driven tasks.

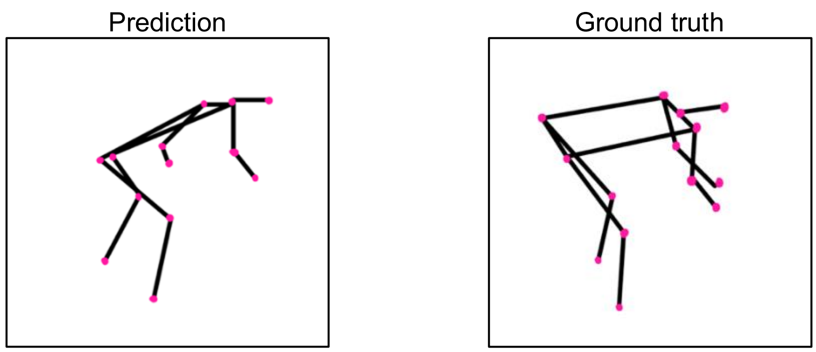
Prediction Ground truth



(a) Prediction and ground truth of Figure 3.



(b) Prediction and ground truth of Figure 4.



(c) Prediction and ground truth of Figure 5.

Figure 6. Comparison of visualization of pose estimation predictions and ground truth for manual demolition tasks

Figure 6 compares pose estimation predictions with manually annotated ground truth data for three manual demolition tasks, including the bending-over task, manual tool operation with hammering, and impact-driven demolition. The left column shows the system's predicted key point detection and skeletal overlays, while the right column presents the ground truth for validation. Table 2 compares the predicted joint angles, computed using the pose estimation model, with the manually estimated ground truth angles for various joints across Figures 3, 4, and 5. The predicted angles are derived from the automated angle computation step, while the ground truth angles are manually measured using an online tool.

Table 2. Comparison of predicted angles and ground truth angles across Figures 3, 4, and 5

	Prediction Angles (Degrees)			**Ground Truth Angles (Degrees)**		
	Figure 3	**Figure 4**	**Figure 5**	**Figure 3**	**Figure 4**	**Figure 5**
Neck	60	72	34	45	63	11
Left Elbow	21	65	26	15	61	35
Right Elbow	13	5	79	21	7	48
Left Knee	24	29	60	15	22	57
Right Knee	23	22	63	8	45	52
Left Trunk	95	34	102	83	39	110
Right Trunk	89	38	111	77	74	103

5.1. Qualitative Validation of Predictions: The system's predictions were assessed by comparing the computed joint angles against manually measured ground truth angles, as shown in Table 2. This comparison reveals a strong alignment between the predicted and ground truth risk levels for most joints, demonstrating the reliability of the pose estimation model. However, discrepancies were observed in certain scenarios, particularly for joints like the right knee and right trunk in Figure 4 and the neck and right elbow in Figure 5, where occlusions, complex backgrounds, or dynamic movements may have influenced the predictions. Despite these deviations, the system effectively highlighted key ergonomic risks by categorizing angles into REBA-based risk levels assessment, supporting its ability to identify hazardous postures and provide valuable insights for ergonomic evaluation.

5.2. Overall System Performance: Integrating pose estimation with REBA risk levels proved to be a robust approach for detecting hazardous postures and quantifying ergonomic risks in manual construction demolition tasks. The system demonstrated adaptability to dynamic construction environments, providing accurate visual feedback that facilitated both immediate risk identification and post-task analysis. Automating the ergonomic assessment process offers a scalable and practical solution for enhancing workplace safety, with the potential to significantly reduce musculoskeletal disorder risks by proactively identifying and addressing hazardous postures.

6. CONCLUSIONS

This study presented a novel approach to ergonomic risk assessment in manual construction demolition tasks by integrating pose estimation techniques with the REBA framework. The proposed system successfully tracked key body joints, calculated critical angles, and identified postural deviations contributing to ergonomic risks. By automating posture detection and providing visual overlays, the system offers an innovative tool for enhancing occupational safety in dynamic construction environments.

Key findings demonstrate the system's capability to effectively classify ergonomic risks into low, medium, and high categories based on established angle thresholds from REBA. Tasks involving repetitive bending and awkward postures, such as bending-over tasks and manual tool operation with hammering, were identified as particularly hazardous. The qualitative validation showed strong alignment between the system's predictions and manually generated ground truth labels, supporting its reliability for ergonomic evaluation. The system has great potential for assessing MSD risks in real-time, identifying hazardous work activities and postures without disrupting work, and proactively recommending interventions, such as using mechanical assistance to reduce worker risks.

This study has several limitations that highlight opportunities for future research. The system's performance was influenced by environmental factors such as lighting, occlusions, and background clutter, which are common challenges in dynamic construction environments. The current approach primarily addresses static postural risks, excluding dynamic factors such as repetitive motion and force exertion, as well as psychosocial elements like workload and job stress. In addition, the system was only capable of assessing angles deviated from neutral body positions and did not account for whether a body part was twisted, side-bending, or the amount of weight a person was handling while performing a task. All of these factors would elevate the risk of developing MSDs. Furthermore, the system does not yet provide real-time feedback, limiting its ability to intervene proactively during task execution. Addressing these limitations will be essential to enhance the system's robustness, scalability, and practical applicability in real-world environments.

While the current system provides robust real-time posture analysis, future work will focus on refining the accuracy of REBA score predictions and further automating the assessment process. Beyond automating REBA scoring, future research will investigate integrating advanced machine learning algorithms to improve the system's adaptability to complex and cluttered construction environments. Additionally, enhancing the system's ability to track multiple workers simultaneously will be a key area of development. Currently, the system focuses on detecting and analyzing a single worker, but future improvements will aim to extend its capabilities to monitor several workers within the same frame, accounting for interactions and movement patterns in group tasks. Future research will also focus on improving the system's capability to track the frequency of repeated hazardous postures using computer vision. While the current system can detect and categorize individual postures, accurately monitoring the recurrence of the same hazardous posture over time remains a challenge, particularly in dynamic construction environments with occlusions and changing camera angles. Deep learning models could also be trained on larger, more diverse datasets to enhance the accuracy of pose estimation under challenging conditions, such as low-light settings or occlusions caused by equipment or other workers. Another avenue for exploration is the development of real-time feedback mechanisms. By integrating wearable devices or augmented reality (AR) technologies, workers could receive immediate visual or haptic alerts about their posture, enabling on-the-spot corrections and reducing the likelihood of injuries.

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