Journal of Mechanical Engineering and Applied Technology, Vol 4 (2) 2026, 105-114
e-ISSN : 3025-2725

Markerless Computer-Vision Joint-Angle Analysis for Ergonomic Risk Assessment of Engineering Students During Bench-Work Practicum

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Submitted: July 1, 2026; Accepted: July 20, 2026; Published: July 25, 2026

Abstract

Bench work (kerja bangku) is a foundational manual-skills practicum in mechanical and manufacturing engineering education. It requires sustained non-neutral postures—forward trunk flexion, downward neck flexion toward the vice, and repetitive upper-limb exertion—that expose students to work-related musculoskeletal disorder (WMSD) risk early in their careers. Conventional ergonomic evaluation relies on manual observation, which is subjective, labour-intensive, and difficult to scale across large student cohorts. This study presents a markerless computer-vision pipeline that estimates body joint angles from ordinary RGB video and automatically derives Rapid Upper Limb Assessment (RULA) scores for students performing bench-work tasks. Two-dimensional pose estimation localized anatomical landmarks; sagittal joint angles for the neck, trunk, upper arm, lower arm, and wrist were computed from landmark coordinates and mapped to RULA segment scores. Thirty engineering students were recorded performing five representative tasks (filing, hacksawing, marking/scribing, chiselling, and hand-tapping). The mean RULA grand score across tasks was 6.0, with 92% of observations falling in action levels 3–4 ("investigate and change"). Vision-derived joint angles agreed with manual goniometry to within a mean absolute error of 4.8°, and RULA grand scores matched an expert assessor within ±1 point in 96.7% of cases (weighted Cohen's κ = 0.82). The results show that markerless computer vision offers a low-cost, objective, and scalable instrument for ergonomics education, posture feedback, and bench-station redesign.

Keywords: *bench work; computer vision; ergonomics; markerless pose estimation; joint angle; RULA; musculoskeletal disorders*

1. Introduction

Bench work, known in Indonesian vocational and engineering curricula as kerja bangku, is among the first hands-on competencies that mechanical and manufacturing engineering students acquire. Working at a fixed bench vice, students practise filing, hacksawing, marking and scribing, chiselling, and hand-tapping to develop dimensional accuracy and tool control. These activities are performed in a standing posture for extended periods and demand repetitive, forceful upper-limb motions combined with a head-down visual focus on the workpiece. Such conditions are biomechanically demanding and are widely recognized as risk factors for work-related musculoskeletal disorders (WMSDs) of the neck, shoulder, back, and wrist [1-3]. Because students perform these activities repeatedly throughout their practical training, incorrect working postures may gradually become habitual and continue into their future professional careers. Providing objective feedback on working posture at an early stage is therefore important, not only to reduce the risk of musculoskeletal injuries but also to develop good ergonomic habits from the beginning. Conventional observational methods, such as the Rapid Upper Limb Assessment (RULA) and the Rapid Entire Body Assessment (REBA), are widely used to evaluate ergonomic risk by assessing body posture during work. However, these methods rely heavily on manual observation and the judgment of trained assessors, making the assessment process time-consuming and susceptible to observer variability. In addition, they are difficult to apply efficiently in educational workshops where many students perform bench work activities simultaneously. Recent systematic reviews have also highlighted that, despite their widespread use, observational assessment methods still face challenges related to reliability, validity, and practical implementation in large-scale ergonomic evaluations [4-6].

Recent advances in computer vision have made it possible to detect and track human body joints directly from video recordings. This technology enables automatic and objective posture assessment without the need for wearable sensors or expensive motion-capture systems. Markerless pose estimation uses a single RGB camera to estimate the positions of body joints, allowing joint angles and ergonomic risk scores to be calculated automatically. Although this approach has been widely studied in industrial and clinical applications, its use in vocational engineering education, particularly during bench work practice, is still limited. In this setting, a low-cost system that is easy to use and provides immediate feedback is highly desirable. This study aims to develop and evaluate a markerless computer vision system for ergonomic assessment during bench work practice. The specific objectives of this study are: (i) to develop a markerless computer vision system that estimates the sagittal joint angles of the neck, trunk, upper arm, lower arm, and wrist from video recordings of students performing bench work; (ii) to automatically calculate RULA segment scores and the final RULA score based on the estimated joint angles, and to determine the ergonomic risk level for five common bench work tasks; and (iii) to evaluate the accuracy of the estimated joint angles and RULA scores by comparing them with measurements obtained using manual goniometry and expert RULA assessment.

2. Materials and Methods

2.1. Participants

Thirty undergraduate mechanical engineering students of Politeknik Negeri Semarang who were enrolled in the first-year bench work practicum participated in this study. Students were included if they were actively attending the course and had no current musculoskeletal injuries. All participants gave informed consent before taking part in the study, and the research was conducted in accordance with the institutional ethical guidelines. Basic anthropometric information, including body height, body weight, and dominant hand, was collected to describe the participants. The height of the workbench and bench vice was not adjusted and remained at the standard laboratory setting to represent the actual learning environment.

2.2. Bench-work Tasks

Five tasks representative of the bench work syllabus were selected because together they span the dominant posture and exertion patterns of the practicum: Filing: Repetitive horizontal stroking with sustained shoulder flexion and forward trunk lean; Hacksawing: Repetitive reciprocating motion with marked trunk flexion and forceful exertion; Marking/scribing: Precision task with pronounced neck flexion and close visual focus; Chiselling / hammering: Impact task with elevated upper-arm posture and wrist deviation; Hand-tapping: Controlled rotational task with sustained elbow flexion and wrist load.

2.3. Video Acquisition

Each bench work task was recorded using a single RGB camera with a resolution of 1080p at 30 frames per second. The camera was mounted on a tripod at approximately hip height and positioned on the participant's dominant working side to obtain a sagittal view of the body. This camera placement provided a clear view of the neck, trunk, shoulder, and elbow movements, which are required for ergonomic posture assessment using joint angles. Lighting conditions were kept as uniform as possible to obtain clear video recordings and improve the accuracy of body keypoint detection. Participants wore black long armed t-shirt and performed the tasks in the same way as during normal laboratory practice so that the recorded postures reflected their natural working behaviour rather than instructed poses. At least 60 seconds of continuous video was recorded for each task to capture representative working postures and postures with the highest ergonomic risk [7-8].

2.4. *Pose Estimation and Landmark Detection*

Each video frame was processed using the MediaPipe BlazePose markerless pose estimation model, while OpenPose was used for comparison [9-10]. The model detected the locations of the main body joints, including the shoulders, elbows, wrists, hips, knees, and ankles, and assigned a confidence score to each joint. Frames with a confidence score below 0.5 or with occluded body joints were removed from the analysis. The detected joint trajectories were then smoothed using a low-pass filter to reduce noise before calculating the joint angles [7].

2.5. *Joint-Angle Computation*

Joint angles were calculated from the smoothed 2D body landmarks obtained from the pose estimation model. For each joint, the angle was calculated using three landmarks, where the middle landmark represented the joint center. he angle was determined from the angle between two vectors using the dot product in Equation (1) [11].

$$\theta = cos^{-1}(\frac{v_1 . v_2}{\|v_1\| \, \|v_2\|}) \tag{1}$$

Where $v_1 = P_A - P_B$ and $v_2 = P_C - P_B$ and P_A, P_B and P_C are the coordinates of three body landmarks (As seen adn illustrated in Figure 1). For example, the elbow angle was calculated using the shoulder, elbow, and wrist landmarks.

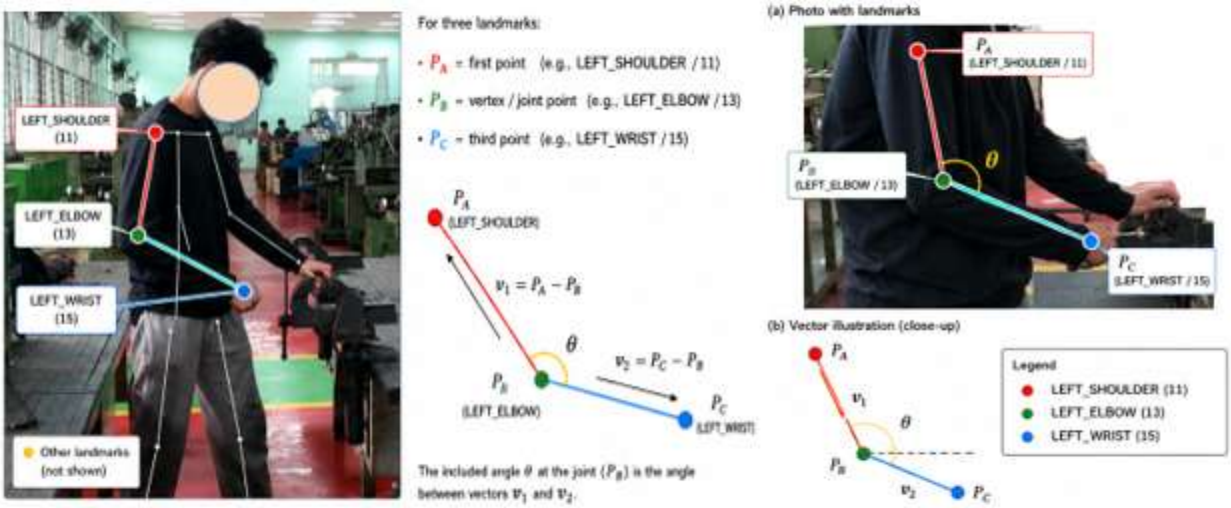

Figure 1. Illustration of three body landmark calculation

The inclination angles of the trunk and neck were calculated relative to the vertical direction using Equation (2).

$$\emptyset = arctan2(\Delta x, \Delta y) \tag{2}$$

Where Δx and Δy are the horizontal and vertical differences between two body landmarks. The trunk angle was calculated from the hip and shoulder landmarks, while the neck angle was calculated from the shoulder and ear landmarks. The upper arm angle was measured relative to the trunk segment. For each participant and each bench work task, the frame representing the highest ergonomic load was selected for the RULA assessment. This approach follows the RULA guideline, which recommends evaluating the posture with the greatest ergonomic risk during the work activity.

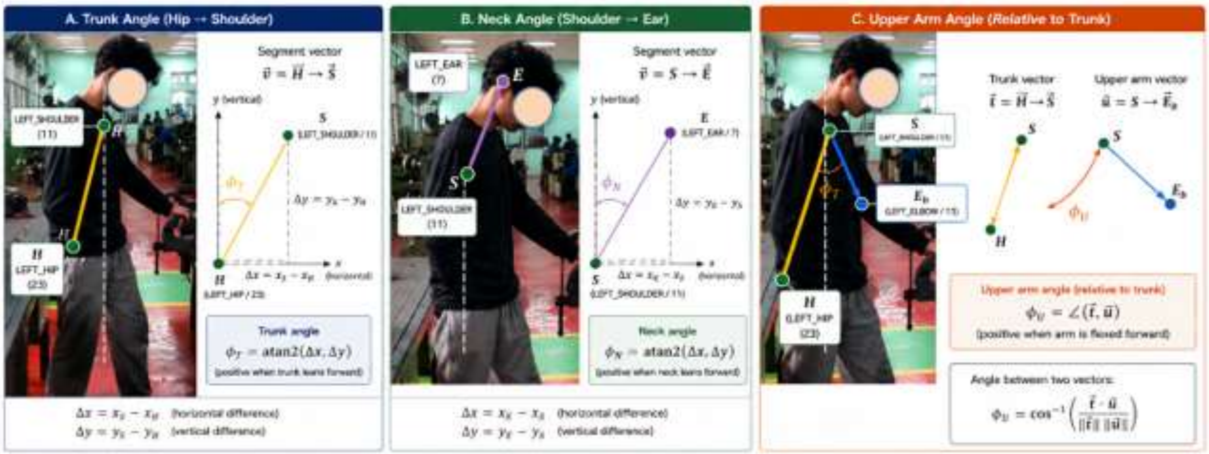

Figure 2. Illustration of inclination trunk and neck inclination angle calculation

2.6. *RULA-Based Ergonomic Scoring*

The joint angle obtained from the pose estimation model were converted into RULA scores based on the standard angle thresholds shown in Table 1 [12]. In the RULA method, body segments are divided into Group A (upper arm, lower arm, wrist, and wrist twist) and Group B (neck, trunk, and legs). Each body segment is assigned a score according to its measured posture. The scores are then combined using the standard RULA lookup tables, with additional adjustments for muscle use and external force or load. Finally, the overall RULA grand score is obtained, ranging from 1 to 7, where higher scores indicate a greater ergonomic risk and a higher priority for corrective action [5,12]. The RULA grand score was interpreted according to the recommended action levels: **1–2** (acceptable posture), **3–4** (further investigation is recommended), **5–6** (changes should be implemented soon), and **7** (immediate corrective action is required).

Additional RULA adjustments for shoulder abduction, shoulder elevation, wrist deviation, trunk twisting, side bending, muscle use, and external load were applied according to the original RULA guidelines [12].

Table 1. RULA posture scoring criteria used in this study (Adapted from McAtamney & Corlett, 1993) [12]

Body Segment	Joint Angle/Posture	Score
Upper arm	-20° to 20°	1
	>20° extension or 20°-45° flexion	2
	45°-90° flexion	3
	>90° flexion	4
Lower arm	60°-100° flexion	1
	<60° or >100°	2
Wrist	Neutral (0°)	1
	0°-15° flexion/extension	2
	>15° flexion/extension	3

Neck	0º-10º flexion	1
	10º-20º flexion	2
	>20º flexion	3
	Extension	4
Trunk	Upright	1
	0º-20º flexion	2
	20º-60º flexion	3
	>60º flexion	4
Legs	Balanced and supported	1
	Unbalanced posture	2

2.7. Validation and Stastitical Analysis

To evaluate the proposed system, a subset of the recorded postures was assessed manually by a certified ergonomics assessor using the RULA method. The corresponding joint angles were also measured manually using a goniometer from the same video frames. The joint angles obtained from the computer vision system were compared with the manual measurements using the mean absolute error (MAE). The automatically generated RULA scores were then compared with the expert RULA scores. The agreement between the two methods was evaluated using the exact match rate, the within ±1 score agreement, and weighted Cohen's kappa (κ). All results are presented as mean ± standard deviation (SD).

3. Result and Discussion

Figure 3 illustrates the markerless pose estimation process used in this study for ergonomic posture assessment during bench work activity.

Figure 3. Markerless pose estimation

Panel (a) shows the original RGB image captured using a single camera during the hacksawing task. Panels (b) and (c) present the body landmarks detected by MediaPipe BlazePose and OpenPose, respectively. Both frameworks successfully identified the main body joints required for posture analysis, including the shoulder, elbow, wrist, hip, and ear. As shown in panel (d), only the landmarks required for joint angle calculation were selected. Specifically, the LEFT_EAR (7) and LEFT_SHOULDER (11) landmarks were used to calculate the neck angle, LEFT_HIP (23) and LEFT_SHOULDER (11) were used for the trunk angle, and LEFT_SHOULDER (11), LEFT_ELBOW (13), and LEFT_WRIST (15) were used to determine the upper arm and elbow angles. These joint angles were subsequently converted into RULA posture scores according to the standard RULA scoring criteria. The figure also demonstrates that a single RGB camera can provide sufficient anatomical information for automatic ergonomic assessment without the need for wearable sensors or marker-based motion capture systems. This simple and low-cost setup makes the proposed approach suitable for use in engineering laboratories and vocational education, where multiple students perform bench work activities simultaneously.

The proposed computer vision system successfully estimated the joint angles of the neck, trunk, upper arm, lower arm, and wrist during five bench work tasks and automatically generated the corresponding RULA scores. Tables 2 and 3 summarize the average joint angles and ergonomic risk levels obtained for each task.

Table 2. Average sagittal joint angles during bench work tasks

Task	Neck	Trunk	Upper Arm	Elbow	Wrist
Filing	28.4 ± 6.1	31.2 ± 7.8	42.5 ± 9.3	78.6 ± 11.2	14.8 ± 5.6
Hacksawing	32.7 ± 7.4	38.5 ± 8.9	48.2 ± 10.1	84.3 ± 12.5	18.3 ± 6.2
Marking/scribing	38.9 ± 8.2	22.4 ± 6.3	25.7 ± 7.8	92.1 ± 10.4	12.5 ± 4.9
Chiselling	24.6 ± 5.8	27.9 ± 7.1	55.3 ± 11.4	71.2 ± 13.1	21.7 ± 7.3
Hand-tapping	35.2 ± 7.9	29.6 ± 7.6	38.4 ± 9.7	88.7 ± 11.8	16.4 ± 5.8

Table 3. RULA segment score and risk category by task

Task	Score A	Score B	Grand	Action	Risk Category
Filing	4	5	6	3	High – change soon
Hacksawing	5	6	7	4	Very high – now
Marking/scribing	3	4	5	3	Change soon
Chiselling	4	4	6	3	High – change soon
Hand-tapping	4	5	6	3	High – change soon

According to Table 2 the mean sagittal joint angles for each task. Hacksawing produced the greatest trunk flexion (38.5°) and elevated upper-arm flexion, while marking/scribing produced the greatest neck flexion (38.9°) owing to the close downward visual focus required for precision layout. Chiselling produced the highest upper-arm flexion (55.3°) and wrist deviation, reflecting the raised-arm impact posture. Among the five tasks, hacksawing showed the largest trunk flexion and one of the highest upper arm flexion angles, indicating a high postural load caused by repetitive force and forward bending. In contrast, marking and scribing resulted in the greatest neck flexion because students had to look closely at the workpiece during precision marking. Chiselling required the largest upper arm elevation and greater wrist movement, reflecting the repetitive impact motion used during the task. These findings indicate that different bench work activities place different mechanical demands on the upper body, although all tasks involve prolonged non-neutral postures.

Table 3 presents the resulting RULA Group A, Group B, grand scores, and action levels. All five tasks fell into action level 3 or higher, indicating that ergonomic intervention is needed. Hacksawing reached a grand score of 7 (action level 4, “change immediately”), driven by the combination of deep trunk flexion, elevated arm posture, and high force. The mean grand score across tasks was 6.0. Similar findings have been reported in previous studies, which identified non-neutral trunk and neck postures as the main contributors to work-related musculoskeletal disorders during manual industrial tasks [4-5].

To evaluate the proposed system, the estimated joint angles and RULA scores were compared with manual measurements obtained from a goniometer (Presented in Table 4). The computer vision system showed good agreement with the reference measurements, with low joint-angle errors and a high level of agreement for the final RULA score. These results are consistent with previous studies showing that markerless pose estimation can provide reliable ergonomic assessment using only a single RGB camera [7,13].

Table 4. Comparation result between computer vision and goniometer

Metric	Value
Joint-angle MAE – neck	4.7°
Joint-angle MAE – trunk	5.2°
Joint-angle MAE – upper arm	4.1°
Joint-angle MAE – elbow	3.8°
Joint-angle MAE – wrist	6.3°
Overall joint-angle MAE	4.8°
RULA grand-score exact agreement	76.7%
RULA grand-score within ±1 point	96.7%
Weighted Cohen’s κ (grand score)	0.82
Pearson r (segment scores, CV vs expert)	0.88

The results demonstrate that the proposed low-cost markerless computer vision system can provide an objective assessment of students' working posture during bench work practice. Compared with conventional manual RULA assessment, the proposed approach reduces observer dependency, provides more consistent posture measurements, and enables ergonomic evaluation of multiple students using only a single RGB camera. These advantages highlight the potential of markerless pose estimation as a practical and scalable tool for ergonomic assessment in educational and industrial environments [14- 15].

Despite these promising results, several limitations should be considered. First, the system relies on a single 2D camera, making it difficult to estimate body movements outside the sagittal plane. Second, landmark occlusion, particularly around the wrist and hand during tool handling, may reduce the accuracy of joint angle estimation. Previous studies have also identified camera position, self-occlusion, and viewing angle as important factors affecting the performance of markerless pose estimation systems [16-17].

Future work should investigate the use of multi-camera or three-dimensional pose estimation techniques to improve the accuracy of joint angle estimation, particularly for complex upper-limb movements. Expanding the study to larger participant groups and developing a real-time ergonomic feedback system would also improve the practical applicability of the proposed approach in vocational engineering education. These directions are consistent with recent reviews that emphasize the need for more robust real-world validation and practical deployment of computer vision-based ergonomic assessment systems [18].

4. Conclusion

This study developed a low-cost markerless computer vision system for ergonomic assessment during bench work practice using a single RGB camera. The proposed method successfully estimated the sagittal joint angles of the neck, trunk, upper arm, lower arm, and wrist, and automatically converted these measurements into RULA scores for ergonomic risk assessment.

The results showed that the proposed system provided joint angle measurements and RULA scores that were in good agreement with manual goniometer measurements and expert RULA assessment. The system was also able to identify differences in ergonomic risk among the five bench work tasks, demonstrating its capability to support objective posture evaluation in vocational engineering education.

Compared with conventional manual assessment, the proposed approach offers a faster, more consistent, and more practical solution for evaluating multiple students without wearable sensors or expensive motion capture systems. This makes the system suitable for routine ergonomic assessment and immediate feedback during practical laboratory sessions.

Future work should improve the robustness of the system by incorporating multi-camera or three-dimensional pose estimation, reducing landmark occlusion, and expanding validation with larger participant groups and different workshop activities. The integration of real-time ergonomic feedback is also expected to further support safer and more effective engineering training.

Acknowledgement

The authors would like to thank the Department of Mechanical Engineering, Politeknik Negeri Semarang, Indonesia, for providing the laboratory facilities and technical support during this study. The authors also sincerely appreciate all students who participated in the bench work experiments and the certified ergonomics assessor for their assistance in the manual RULA evaluation and data validation. Their valuable contributions made this research possible. This research was funded by the Politeknik Negeri Semarang (DIPA Polines) through the Penelitian Terapan Pratama (PTP) Program under Grant No. 0214/PL4.7.2/SK/2025.

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