Risk Assessment of Musculoskeletal Disorders Using Artificial Intelligence

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Abstract. Agricultural ergonomics employs methods such as Rapid Upper Limb Assessment (RULA) and Rapid Entire Body Assessment (REBA) to assess postural risks. However, these methods may be inaccurate and time-consuming. The objective of this study is to compare the effectiveness of Artificial Intelligence (AI), specifically a software based on MediaPipe, with conventional methods (RULA-REBA) to identify and assess ergonomic risks due to postures in rice agriculture. The methodology employed involved the development of AI software with MediaPipe, which was designed to detect postures in real time. This model was capable of identifying 33 anatomical points, thereby enabling detailed analysis of movement and posture. The results demonstrated that the AI outperformed RULA and REBA in detecting forced postures. Furthermore, it provided faster and more accurate assessments. The findings indicated that AI could be a valuable tool in agricultural ergonomics, potentially outperforming traditional methods. This could significantly improve working conditions and reduce musculoskeletal disorders among farmers.

1 Introduction

Musculoskeletal disorders (MSDs) are one of the most common occupational health problems in recent years, according to the Global Burden of Diseases, Injuries and Risk Factors Study (GBD), being the second leading cause of non-fatal disability [1]. These disorders affect millions of people worldwide, especially employees performing manual activities. In particular, rice farming involves various awkward postures that increase the risk of MSDs. Conventional methods, such as RULA and REBA, although useful, may be limited in accuracy and agility, requiring more effective alternatives.

Among the most significant issues are those related to musculoskeletal disorders, including back pain, tendonitis, cervical pain, and wrist problems [1–5]. These are prevalent due to prolonged awkward postures that employees maintain, mainly due to a lack of mechanization, the use of tools, the division of labor, and the adoption of awkward postures in tasks such as dividing, providing, and transplanting. Additionally, factors such as work experience, age, and gender contribute to the prevalence of these musculoskeletal disorders. This not only affects health but also productivity in any occupation, with a particular impact on agricultural activities.

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Other studies [4, 6–9] have also confirmed similar ailments attributed to a lack of mechanization and awkward postures. The importance of adapting agricultural ergonomics was also discussed in works pointing out differences between developed and developing countries [10]. Moreover, the necessity for the implementation of regulations such as ISO 11228-3 in Chile for the effective management of these disorders emphasizes the importance of regular ergonomic training and assessments to mitigate these risks [11–13].

A review of research in various global agricultural contexts has identified the urgent need to address ergonomic risks and improve working conditions in order to prevent musculoskeletal disorders among field workers. A study of Colombian farmers using the REBA method identified high ergonomic risk in the task of weeding [14]. Another study noted variable risks in postharvest activities, highlighting the need for interventions in medium-risk tasks such as shelling and cutting [15]. Concurrently, a prevalence of musculoskeletal symptoms has been observed in Iran [16], with a higher incidence among women and those engaged in specific agricultural tasks. Finally, a study conducted in Bhaktapur, Nepal, reported that 36% of farmers suffered from back pain due to overexertion [17].

The collective findings underscore the pressing need to implement sustained, culturally sensitive ergonomic interventions, which should be supported by both government and corporate policies. The goal of these interventions is to improve health and safety standards in the global agricultural sector.

The adoption of artificial intelligence (AI)-based technologies and automated ergonomic tools in agriculture has led to significant advancements in reducing physical strain and injury prevention in the sector [18–20]. These developments have demonstrated the potential of automated RULA-based assessments and computer vision systems in improving working conditions. Despite these advances, ergonomic challenges such as musculoskeletal disorders caused by vibration, noise, and poor posture still persist [2, 21] underscoring the necessity for continuous monitoring and training. Indeed, the use of sensorless AI has improved ergonomics in medical settings [3], suggesting its usefulness in surgical training and reinforcing the importance of ergonomics in various professional settings.

In the context of rice farming, the introduction of artificial intelligence (AI)-based ergonomic risk assessment software raises several key issues that need to be addressed. First, it is critical to determine the accuracy of these AI systems and posture detection models in identifying ergonomic risks by comparing them to traditional assessments performed by occupational risk prevention experts. This comparison will not only assess the technology's ability to accurately identify postures that could lead to musculoskeletal disorders (MSDs), but also whether AI results can improve or complement existing methods.

In addition, it is important to explore how the implementation of automated assessment using AI can contribute to the early detection and prevention of MSDs by investigating whether these tools can more quickly and accurately identify hazardous postures commonly faced by farmers. Finally, it is critical to address the challenges and limitations of integrating this advanced technology into the agricultural environment. This includes overcoming technical, operational and adaptability hurdles, and identifying key areas that require further development and improvement for effective implementation of the software in agricultural settings.

By demonstrating the superiority or complementarity of AI over conventional methods, this study could not only improve ergonomic assessment practices, but also make a significant contribution to reducing the incidence of MSDs among farmers, thereby improving their quality of life and work efficiency.

The following section presents the methodology applied, based on an advanced artificial intelligence software and the MediaPipe framework, which is designed to detect and evaluate postures in real time and could offer superior accuracy and speed compared to the traditional RULA and REBA methods. Subsequently, the results obtained by applying the aforementioned methods are presented, followed by a discussion and a conclusion that allows associating the results of other related studies, as well as the limitations of the work.

2 Method

This section describes the methodology employed to examine a system for preventing poor ergonomic posture. Figure 1 illustrates the pipeline that starts analyzing input video material from both stored files and real-time transmissions. The videos are processed frame by frame. MediaPipe's technology for detecting key body points allows the system to calculate Euclidean distances to determine body part angles such as neck, torso, and knee inclinations. The assessment methodology conforms to the standards RULA and REBA methods. The result is a detailed estimate of the ergonomic risk associated with each frame of the video. To validate the effectiveness of the developed system, a comparative analysis of the automated results was performed with ergonomic evaluations performed by human experts, using the same sets of videos. Each video was subjected to a detailed evaluation following the RULA and REBA methods, thus providing a reference data set against which the results of the artificial intelligence system were contrasted.

Figure 1. The pipeline for automatic risk assessment: Input video or streaming is analyzed frame by frame to identify body landmarks using Media Pipe. Then angles are calculated according RULA and REBA standards. The output is the ergonomic risk.

2.1 Dataset

The data section of the article consists of a set of 20 videos taken at the rice planting site. Each video portrays an individual farmer during the planting process in the tasks of dividing, proportioning, and planting. The recordings document three critical activities: dividing, proportioning, and planting. The videos, averaging two minutes in length, are in MP4 format and recorded at 30 frames per second to ensure a smooth and detailed observation of the work practices. The videos are 368 pixels wide by 640 pixels high, with a consistent data rate of 765 kbps to optimize image quality while maintaining data handling efficiency.

In the preprocessing stage, the original frames of the videos are not modified; instead, selective filtering is applied using OpenCV. This filtering is governed by an adjustable parameter that controls the rate of processed frames. This strategy ensures optimized operational efficiency, adapting to the specific needs of the study without compromising data quality and representativeness. In the experiments conducted in this study, the OpenCV filtering parameter was set to process only five frames per second of each video. This approach reduces the amount of data to be analyzed by focusing on a representative sample that provides sufficient insight into the farmer's activity without the need for unnecessary processing of redundant information.

2.2 Pose detection with AI

Pose detection, also referred to as pose estimation, is a computer vision technology that identifies a person's position and orientation in images and videos by marking key points

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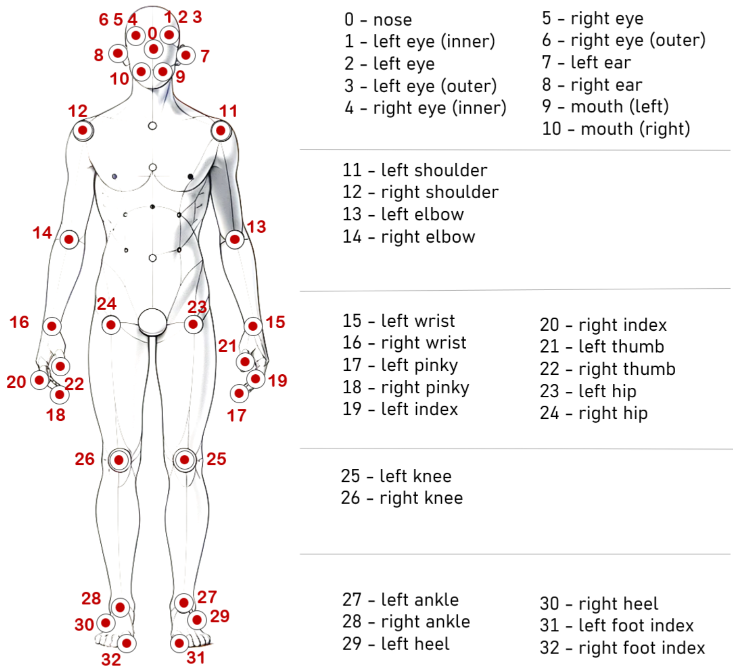

Figure 2. List of the landmarks detected by the posture detection model of the MediaPipe framework in the human body.

on the human body, such as joints. MediaPipe, an open-source media processing library created by Google, implements pose detection using convolutional neural networks (CNNs) trained on large datasets of images and videos featuring diverse human postures. Previous research has demonstrated the effectiveness of the MediaPipe posture detection model in identifying and analyzing human postures with high accuracy [5]. These technologies enable detailed analysis of movements and postures in real-world work environments, overcoming the limitations of traditional methods.

Figure 2 illustrates the 33 anatomical landmarks [22] or key points identified by the posture recognition model. These landmarks include joints and body segments such as the head, shoulders, elbows, wrists, hips, knees, and ankles. Each landmark represents the two-dimensional (x, y) coordinates relative to the coordinate system of the analyzed image or video, enabling a detailed analysis of posture and movement.

2.3 Angle estimation

Table 1 describes all the angles calculated for later use in the estimation of RULA and REBA scores. To illustrate, let's consider the left forearm angle (FL). The landmarks used to determine this angle are the left shoulder (landmark 11), the left elbow (landmark 13), and the left wrist (landmark 15). The distance $d_{p,q}$ is the straight line distance between any two landmarks p and q, measured in the plane of motion. This is given by the Euclidean distance formula, which computes the distance based on the x and y coordinates of these points.

$$d_{p,q} = \sqrt{(X_p - X_q)^2 + (Y_p - Y_q)^2} \tag{1}$$

Table 1. MediaPipe key points used to calculate the angles according to the body parts defined by the RULA and REBA.

Body part angle	Abbreviation	Involved landmarks
Left arm	AL	$\angle 13, 11, 23$
Right arm	AR	$\angle 14, 12, 24$
Left shoulder	SL	$\angle 12, 11, 13$
Right shoulder	SR	$\angle 11, 12, 14$
Left forearm	FL	$\angle 11, 13, 15$
Right forearm	FR	$\angle 12, 14, 16$
Left hip side	HL	$\angle 11, 23, 25$
Right hip side	HR	$\angle 12, 24, 26$
Left knee	KL	$\angle 23, 25, 27$
Right knee	KR	$\angle 24, 26, 28$
Left wrist	WL	$\angle 13, 19, 15$
Right wrist	WR	$\angle 14, 20, 16$
Left wrist deviation	UL	$\angle 17, 15, 19$
Right wrist deviation	UR	$\angle 18, 16, 20$
Neck flexion	NF	$\angle 0, 12, 11$
Neck bending left	NL	$\angle 11, 7, 12$
Neck bending right	NR	$\angle 11, 8, 12$
Trunk flexion left	XL	$\angle 23, 11, 25$
Trunk flexion right	XR	$\angle 24, 12, 26$
Trunk twisting left	TL	$\angle 23, 11, 24$
Trunk twisting right	TR	$\angle 23, 12, 24$

These distances correspond to the lengths of the sides of the triangle formed by the three landmarks. For instance, $d_{11,13}$ is the distance between the shoulder and the elbow, effectively representing the length of the upper arm. Similarly, $d_{13,15}$ represents the length of the forearm, and $d_{11,15}$ is the hypotenuse of the triangle, stretching from the shoulder directly to the wrist.

By applying the law of cosines in Equation 2, we can determine the angle at the elbow joint. This angle reflects the degree of forearm flexion and is a critical component in evaluating the ergonomic risk of a worker's posture.

$$FL = \arccos\left(\frac{d_{11,13} + d_{13,15} + d_{11,15}}{2 \cdot d_{11,13} \cdot d_{13,15}}\right) \tag{2}$$

Thus, the distances $d_{p,q}$ are fundamental to calculating the specific angles which form the basis for the RULA and REBA scoring system, providing a quantifiable measure to assess ergonomic risk.

2.4 RULA and REBA scores

The methodology combines AI software with RULA and REBA. This integration provides a dynamic and accurate assessment of ergonomic risk. Figure 3 shows the angles and positions marked by the software during the division, distribution and planting operations. The

Table 2. Score assignment thresholds that define the risk level defined by RULA and REBA standards.

Body member	Angle used	Position	Score
Arm position	$[AL, AR]$	$(-20°, 20°)$	+1
		$(-\infty, -20°) \vee (20°, 45°)$	+2
		$(45°, 90°)$	+3
		$(90°, \infty)$	+4
Arm abduction	$[SL, SR]$	$(110°, \infty)$	+1
Forearm position	$[FL, FR]$	$(60°, 100°)$	+1
		$(-\infty, 60°) \vee (100°, \infty)$	+2
Forearm to the side	$[SL, SR]$	$(25°, \infty)$	+1
Wrist position	$[WL, WR]$	$0°$	+1
		$(0, 15°)$	+2
		$(15°, \infty)$	+3
Wrist radial / ulnar	$[UL, UR]$	$(-\infty, 30°)$	+1
Neck flexion	$[NF]$	$(0°, 10°)$	+1
		$(10°, 20°)$	+2
		$(20°, \infty)$	+3
		$(-\infty, 0°)$	+4
Head rotation	$[NL, NR]$	$(1°, 5°)$	+1
Head lateral tilt	$[NL, NR]$	$(30°, 45°)$	+1
Trunk flexion	$[XL, XS]$	$\approx 0°$	+1
		$(1°, 20°)$	+2
		$(20°, 60°)$	+3
		$(60°, \infty)$	+4
Trunk rotation	$[TL, TR]$	$(1°, 5°)$	+1
Trunk lateral tilt	$[TL, TR]$	$(30°, 45°)$	+1
Legs	$[HL, HR]$	$(100°, 180°)$	1
	$[HL, HR] \wedge [KL - KR]$	$(100°, 180°) \wedge (0°, 5°)$	1
	$[HL, HR] \wedge [KL - KR]$	$(100°, 180°) \wedge (5°, \infty)$	2

angles are calculated on the basis of Table 1. The thresholds [19, 23, 24] defined in Table 2 correspond to the RULA and REBA standards for assigning the risk level.

RULA employs a series of specific body angle measurements to assess the ergonomic risk associated with upper extremity and torso postures. For example, arm postures (AL, AR) are evaluated based on specific angles, with a scoring system that assigns more points to postures that are considered higher risk. An arm angle of between -20° and 20° is assigned one point, while an angle greater than 90° is assigned four points, indicating a higher ergonomic risk. Similarly, wrist position (WL, WR) and wrist deviation (UL, UR) are also assessed and scored based on their alignment. The scores are then compared to obtain a total score for each group (arm group and neck/trunk group). The total score is then used to identify the level of action required, according to the consolidated RULA table.

REBA extends the assessment to the entire body, including the legs and feet, in addition to the areas covered by RULA. As in RULA, specific body part angles are measured, such as trunk flexion (XL, XR) and trunk rotation (TL, TR). A score is assigned based on the ergonomic risk of the posture. For example, trunk flexion close to 0° receives one point, while flexion greater than 60° receives four points. The scores for each body segment are then compared to tables defined for the upper and lower extremities that are subsequently adjusted for additional factors such as load and grip. Finally, a consolidated REBA score table is used to determine the urgency of needed ergonomic interventions.

2.5 Evaluation

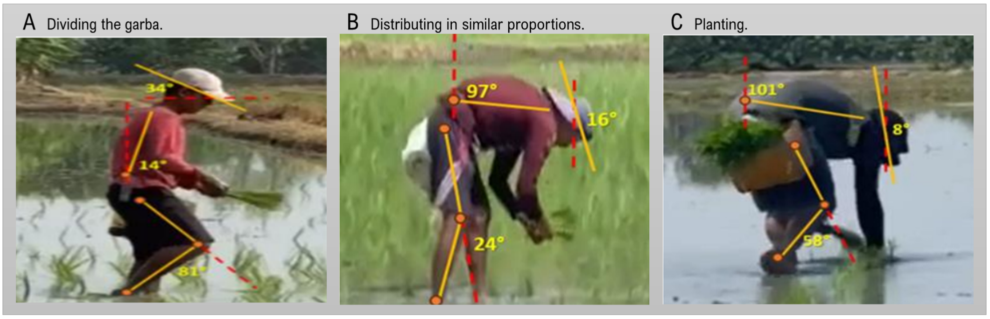

Figure 3. The system in test mode plots each frame with estimated angles. A: the farmer is dividing the garba with trunk flexion 14º. B: is distributing proportionally with trunk flexion 14º. C: is plating with trunk flexion 101º.

The evaluation process analyzed the activities of 20 workers during rice planting using the transplanting technique, specifically for three tasks: A) dividing the garba, B) distributing in equal parts and C) planting. The figure 5 illustrates these activities, in which the system in test mode plots the angles in degrees of the workers' postures. This test mode is crucial, as it facilitates real-time ergonomic visualization and evaluation, providing an interactive tool for immediate posture adjustment and correction. When the software operates outside the test mode, it does not record video images, limiting itself to capturing specific angles and calculating the resulting ergonomic risk.

The applied experimental design examines ergonomic risk assessment methodologies, specifically contrasting the efficacy of the manual/traditional method performed by experts with the artificial intelligence (AI) technique under both the RULA and REBA standard schemes.

A single worker was selected for a focused ergonomic evaluation for each task, including dividing, distributing, and planting. Two well-established manual methods, RULA and REBA, were administered by an ergonomic expert to evaluate the worker's posture. The expert's assessment involved a step-by-step analysis of the worker's movements and postures, capturing the intricacies of dividing, distributing and planting. At the same time, the same task was analyzed using AI-based software developed with MediaPipe. This software pinpointed key body angles by identifying and tracking anatomical landmarks on the worker's body frame by frame during the selected task. Special emphasis was placed on the accuracy of angle detection around critical regions such as the torso, neck, knees, and arms.

The expert performed a manual validation by comparing the angles derived by the AI software with those observed during the manual assessment. This cross-validation was used to assess the accuracy of the software in real-time posture analysis. The frames captured by the AI software, indicating the angles at which the selected activity was performed, provided a visual and quantitative reference for the expert to confirm or challenge the accuracy of the AI. The design of this experiment sheds light on the reliability of AI software in ergonomic risk assessment, specifically its accuracy in reflecting expert judgment about posture-related risks.

3 Results

3.1 Artificial Intelligence (AI)

The results of the automatic evaluation exhibit a lower concentration of scores, which indicates greater consistency in the assignment of risk levels by artificial intelligence. Another variable that was validated is the percentage of average time required for the evaluation applying AI. This allows for a reduction of the time required for the evaluation process. The time required for evaluators to complete their tasks was reduced by 60%, allowing them to perform other tasks while the machine was processing the videos to be analyzed. The reduction in the time required by a single individual to conduct ergonomic risk assessments has enabled the evaluation of a greater number of farmers with the same time commitment to activities related to rice cultivation.

3.2 AI vs RULA

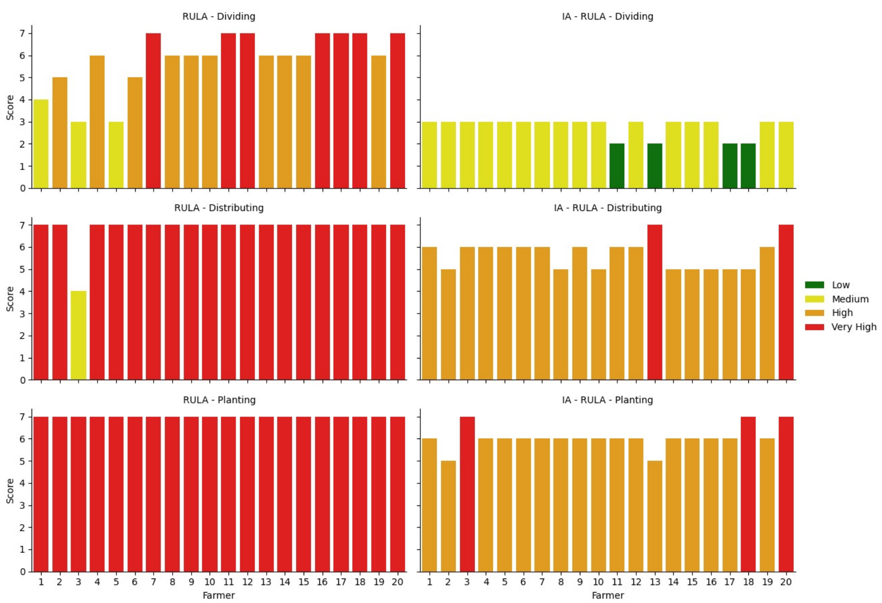

Figure 4. Method RULA vs AI RULA

A comparison of the results of the divide activity reveals a significant discrepancy in the risk levels identified by the experiments. For RULA, this activity reflected 85% of high to very high levels, while in AI it reflected 80% of medium levels. The remaining percentage for RULA is medium (15%), and for AI it reflected an acceptable level (20%). These results indicate a varied need for intervention, ranging from immediate postural corrections to more detailed assessments.

The RULA method was employed to assess the risk associated with the "distribute" activity. The results indicated that the risk level was classified as "very high" for 95% of the farmers. Conversely, the AI identified a "high" risk level, which was observed in 90% of the farmers. These findings suggest that the two methods yielded comparable results, with minimal differences in the level of risk. This observation does not impact the effectiveness of the intervention to reduce the musculoskeletal effects of the worker. In other words, the two results indicate the necessity of correcting the posture as soon as possible.

In the final activity, "planting," 100% of farmers exhibited a high risk level for RULA. However, with AI, 85% exhibited a high level and 15% exhibited a very high level. Both methods underscore the urgency of implementing immediate postural corrections to mitigate the associated ergonomic risks, as illustrated in Figure 4.

3.3 AI vs REBA

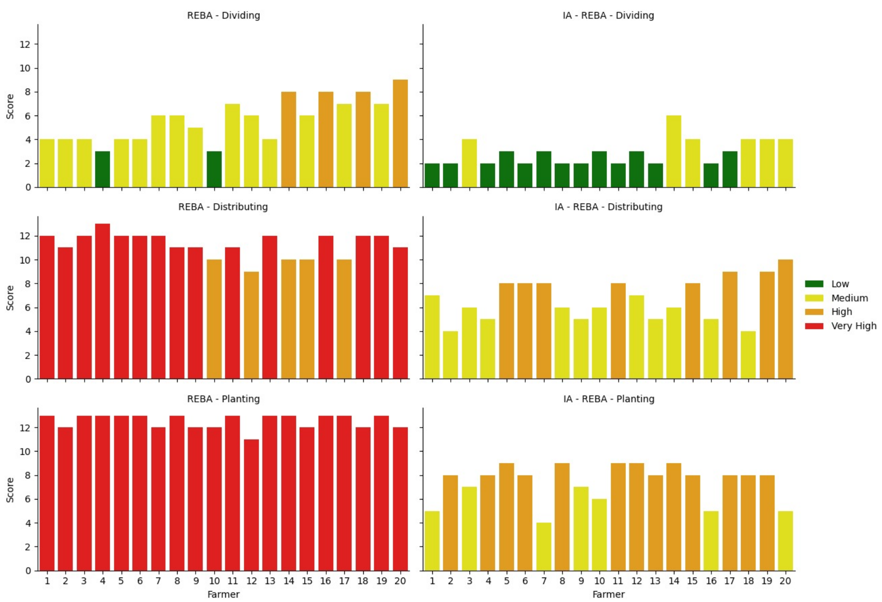

Figure 5. Method REBA vs AI REBA

In the activity evaluated, "dividing" for REBA, 70% corresponded to the medium level. Conversely, for AI, 70% corresponded to the low level, indicating a perception of lower overall risk in this activity compared to REBA. This suggests that a variety of interventions ranging from moderate to low may be appropriate.

The evaluation of the "distribute" activity yielded a result indicating a variation in the risk level as determined by the applied method. In REBA, 75% of the results revealed a very high risk level. In contrast, the AI revealed 60% of results with a medium level, while 40% showed a high level. This result indicates that, in comparison to REBA, AI presents a reduced perception of urgency in the necessary interventions. Consequently, AI offers a potentially more detailed and varied analysis of the risk positions.

The activity of "planting" represents a variation in risk level between the two methods. The application of REBA corresponded to a very high risk level, whereas IA reflected a combination of high and medium levels (65% and 35% respectively). While both require intervention, AI indicates a lower immediacy in the need for correction postulate compared to REBA.

The results show that there is a difference of one level of risk between the evaluation performed with REBA and the application of AI. This difference is evidenced by the fact that the calculation of angles using AI presents variations in relation to the frames per seconds of the analyzed videos compared to the traditional method, as shown in Figure 5.

4 Discussion

4.1 AI-RULA

When comparing RULA and AI, differences in risk assessment are observed. RULA tends to classify more cases as high risk compared to AI. AI provides a more balanced and detailed perception of risk. It uses advanced measurements and subtle motion capture to identify risky postures. This pattern of differences may be influenced by technological developments in ergonomic assessment as discussed in the literature review.

In the "divide" activity, RULA demonstrated a more dispersed distribution of risk levels in contrast to AI, which tended to rate the majority of cases as medium risk. This discrepancy can be attributed to AI's continuous analysis capability. This finding is analogous to the observations made in the study by [25], which demonstrated the effectiveness of the Azure Kinect camera in accurately capturing critical angles. Another advantage is evident in the method presented by [19], which employs computer vision to perform automated, simultaneous ergonomic assessments. These advances demonstrate how technology can enhance the accuracy of ergonomics.

For the "distribute" activity, RULA saw a very high level of risk that required immediate correction. The AI rated the majority as high risk, indicating less urgency. This difference suggests that the AI processes the data more thoroughly than RULA. [26] and [20] show that advanced technologies such as Kinebot and computer vision improve accuracy. They use deep learning algorithms for more detailed and frequent analysis. Compared to RULA, these methods are less subjective. AI enables more accurate and realistic risk assessment. These technological advances better reflect the complexity of work postures.

For the "transplant" activity, both methods assigned a high and very high risk levels to all cases. Both methods showed consistency in the identification of high-risk situations. This is aligned with what was observed in the study by [27] and with the findings of [3], which highlighted the ability of OpenPose technology to perform accurate and rapid assessments, facilitating early and effective intervention in critical situations.

In addition, studies such as [28] highlight adaptive and participatory ergonomic interventions that complement IA. IA customizes assessments with specific data, improving accuracy and acceptance. This increases the effectiveness of preventive measures among workers.

The authors of this study suggest that the differences between RULA and AI are partly due to the inherent nature of each method. RULA uses static and subjective judgments. AI adapts algorithms for dynamic and contextual risk detection. This adaptability is critical in agricultural environments where risks vary across tasks and seasons.

The integration of AI in ergonomic assessment is progressing towards precision and less invasive, adapting to current work environments. Consistency between RULA and IA in high-risk tasks shows their effectiveness. Variations highlight the importance of selecting the appropriate method according to the context. Thus, future research should focus on optimizing the integration of these technologies to maximize ergonomic benefits in all application areas.

4.2 AI-REBA

The comparative analysis between REBA and AI revealed significant differences in risk calibration. These can be attributed to the methodologies used and recent technological advances in ergonomics.

For the "splitting" activity, IA showed lower perceived risk than REBA, suggesting a need for more varied intervention. This ability of AI to adjust assessments to actual risk may be due to its advanced technology, which allows it to capture and analyze subtle variations in postures and movements, an advantage also noted by [29] in using deep learning to improve the accuracy of ergonomic assessments.

For the "provide" activity, REBA identified a higher percentage of cases as very high risk compared to IA, which showed a more balanced risk distribution. IA analyzes postures and movements in detail, providing realistic and less conservative assessments, similar to the observations of [20], who highlighted the effectiveness of automated systems such as "Quick Capture" in accurate and rapid ergonomic assessment.

In the "transplant" activity, both methods agreed in identifying high risk, although AI discriminated more between high and medium risk levels. This AI approach may reflect a better ability to implement accurate and personalized interventions, consistent with studies such as [27] that use motion capture technologies for accurate, noninvasive, real-time assessment.

In [30], they developed a semi-automated AI-based tool that improves accuracy and reduces assessment time by quickly identifying hazardous postures. This is similar to the results of IA in this study, where the technology allows for more accurate differentiation of risk levels. The authors suggest that IA enables continuous and dynamic assessments that outperform traditional methods. REBA, which is based on static assessments, does not capture the true complexity of postures. AI processes large amounts of data in real time, allowing for more detailed analysis. This improves the accuracy and efficiency of ergonomic assessments. It also reduces subjective bias and optimizes the timeliness and appropriateness of interventions.

4.3 AI-RULA-REBA

This study found early limb problems in rice harvesters. The use of RULA, REBA or AI shows significant ergonomic risks in this trade. Although there are differences in the evaluation of each method, ergonomic problems affect the back, neck and shoulder [14]. It is essential to implement control or mitigation measures immediately. [31] suggests obtaining rapid results for early detection of occupational diseases. The use of AI also allows for immediate recommendations and risk control. This improves the work environment and minimizes health impacts.

The automated scores show a more accurate distribution of scores, from 2 to 10 with a mean of 5.68. This suggests that the IA assigns more uniform risk levels than REBA or RULA, which show very high risks with scores from 11 to 13 and a mean of 12.6. The automated assessment gave a lower score of 7.3, indicating a lower risk, although it does not take into account the handling of hazardous tools. The professionalism of the assessor is essential to the accuracy of the data, which is crucial to validate the results of any assessment, as [32] noted.

According to [33] y [34], the adaptability of IA extends to other areas of work, demonstrating its effectiveness in different rice farming contexts. Incorporating AI into ergonomic assessments improves accuracy and personalizes interventions. This technology reduces ergonomic risks and personalizes safety in agriculture. The integration of new technologies is essential to improve occupational health and safety.

4.4 Limitations

The study highlights the challenges of applying AI to ergonomic risk assessment. It is critical to compare its accuracy with traditional methods such as RULA and REBA. Although these methods are subjective, they set a high industry standard. Any new technology must meet or exceed these standards to be effective. This underscores the importance of accuracy and feasibility in ergonomic improvement.

In addition, the use of AI in the early detection and prevention of musculoskeletal disorders faces significant hurdles in its integration into the agricultural environment. These include overcoming technical and operational limitations, making the necessary adjustments to adapt the technology to different field conditions, and providing adequate training to users. These barriers underscore the importance of continuous and careful development to ensure that the implementation of IA is not only technologically feasible, but also effective in improving working conditions and worker health.

5 Conclusions

In terms of accuracy, the results indicated that AI software based on MediaPipe demonstrated superior performance compared to RULA and REBA. In the "split" task, AI identified 80% of cases as medium risk, while RULA marked 85% of cases as high risk. These differences highlight the superior accuracy of AI, as it provides a more balanced and detailed risk assessment, which is crucial for planning appropriate and timely interventions.

Furthermore, the integration of AI into automated assessments has reduced assessment time by 60%, thus accelerating the analysis of occupational hazards. This advancement allows for more frequent analysis, which is crucial for the early detection and prevention of musculoskeletal disorders in farmers. By acting early, the development of chronic injuries in farmers can be prevented, thus improving their well-being. AI demonstrates high consistency in assigning risk levels, thus optimizing the identification of hazardous conditions.This consistency is superior to that of traditional methods and facilitates the prioritization of necessary interventions. In addition to streamlining assessments, AI improves the accuracy and effectiveness of ergonomic interventions.

The adoption of AI technology in agriculture, particularly in rice cultivation, presents significant advantages but also faces important challenges. These include adapting the technology to varying field conditions, overcoming technical limitations such as the accuracy of analysis in natural environments, and providing adequate training to users. Additionally, difficulties exist in fully capturing the profiles of those being assessed through video, which can compromise the accuracy of the assessments. These challenges underscore the need for continuous and meticulous development leaving a gap for future studies that consider these limitations to improve working conditions and worker health.

References

1. T.K. Gill, M.M. Mittinty, L.M. March, J.D. Steinmetz, G.T. Culbreth, M. Cross, J.A. Kopec, A.D. Woolf, L.M. Haile, H. Hagins et al., Global, regional, and national burden

of other musculoskeletal disorders, 1990–2020, and projections to 2050: a systematic analysis of the global burden of disease study 2021, The Lancet Rheumatology **5**, e670 (2023).
2. Fathallah, Musculoskeletal disorders in labor-intensive agriculture, Elsevier **41**, 738 (2010). https://doi.org/10.1016
3. B.C. Hamilton, M.I. Dairywala, A. Highet, T.C. Nguyen, P. O'Sullivan, H. Chern, I.S. Soriano, Artificial intelligence based real-time video ergonomic assessment and training improves resident ergonomics, The American Journal of Surgery **226**, 741 (2023).
4. R. Jain, M.L. Meena, G.S. Dangayach, A.K. Bhardwaj, Risk factors for musculoskeletal disorders in manual harvesting farmers of rajasthan, Industrial health **56**, 241 (2018).
5. J.W. Kim, J.Y. Choi, E.J. Ha, J.H. Choi, Human pose estimation using mediapipe pose and optimization method based on a humanoid model, Applied Sciences **13**, 2700 (2023).
6. M. McMillan, C. Trask, J. Dosman, L. Hagel, W. Pickett, S.F.I.C.S. Team et al., Prevalence of musculoskeletal disorders among saskatchewan farmers, Journal of agromedicine **20**, 292 (2015).
7. M. Biazus, C.F. Moretto, A. Pasqualotti, Relationship between musculoskeletal pain complaints and family agriculture work, Revista Dor **18**, 232 (2017).
8. E. Sombatsawat, T. Luangwilai, P. Ong-artborirak, W. Siriwong, Musculoskeletal disorders among rice farmers in phimai district, nakhon ratchasima province, thailand, Journal of Health Research **33**, 494 (2019).
9. M. Sharifirad, A. Poursaeed, F. Lashgarara, S.M. Mirdamadi, Risk factors for musculoskeletal problems in paddy field workers in northern iran: A community-based study, Journal of Research in Medical Sciences: The Official Journal of Isfahan University of Medical Sciences **27** (2022).
10. O'Neill, Ergonomics in industrially developing countries: does its application differ from that in industrially advanced countries?, Applied Ergonomics **3**, 631 (2000). https://doi.org/10.1016/S0003-6870(00)00033-8
11. H.I. Castellucci, C. Viviani, P. Hernández, G. Bravo, M. Martínez, J. Ibacache, Á. Bartsch, Developing countries and the use of iso standard 11228-3 for risk management of work-related musculoskeletal disorders of the upper limbs (wrmsds-uls): The case of chile, Applied Ergonomics **96**, 103483 (2021).
12. T.S. Ogedengbe, O.A. Abiola, O.M. Ikumapayi, S.A. Afolalu, A.I. Musa, A.O. Ajayeoba, T.A. Adeyi, Ergonomics postural risk assessment and observational techniques in the 21st century, Procedia Computer Science **217**, 1335 (2023).
13. A. Kongtawelert, B. Buchholz, D. Sujitrarath, W. Laohaudomchok, P. Kongtip, S. Woskie, Prevalence and factors associated with musculoskeletal disorders among thai burley tobacco farmers, International Journal of Environmental Research and Public Health **19**, 6779 (2022).
14. M. Rodríguez Espitia, Ph.D. thesis, Corporación Universitaria Minuto de Dios (2018)
15. P.A. Rojas Nieto, A.L. Sierra Rubiano, L.D. Gallego Garcia, Ph.D. thesis, Corporación Universitaria Minuto de Dios (2019)
16. I. Dianat, D. Afshari, N. Sarmasti, M.S. Sangdeh, R. Azaddel, Work posture, working conditions and musculoskeletal outcomes in agricultural workers, International Journal of Industrial Ergonomics **77**, 102941 (2020).
17. P.K. Mahto, B.B. Gautam, Prevalence of work-related musculoskeletal disorders in agricultural farmers of bhaktapur district, nepal, International Journal of Occupational Safety and Health **8**, 3 (2018).

18. G.K. Nayak, E. Kim, Development of a fully automated rula assessment system based on computer vision, International Journal of Industrial Ergonomics **86**, 103218 (2021).
19. M. MassirisFernández, J.Á. Fernández, J.M. Bajo, C.A. Delrieux, Ergonomic risk assessment based on computer vision and machine learning, Computers & Industrial Engineering **149**, 106816 (2020).
20. X.X. Li Li, Tara Martin, A novel vision-based real-time method for evaluating postural risk factors associated with musculoskeletal disorders, Applied Ergonomics **87** (2020). https://doi.org/10.1016/j.apergo.2020.103138.
21. B. Qiu, Y. Zhang, H. Shen, J. Zhou, L. Chu, Ergonomic researches in agricultural machinery-a systematic review using the prisma method, International Journal of Industrial Ergonomics **95**, 103446 (2023).
22. A.K. Singh, V.A. Kumbhare, K. Arthi, Real-time human pose detection and recognition using mediapipe, in *International Conference on Soft Computing and Signal Processing* (Springer, 2021), pp. 145–154
23. D. Battini, A. Persona, F. Sgarbossa, Innovative real-time system to integrate ergonomic evaluations into warehouse design and management, Computers & Industrial Engineering **77**, 1 (2014). https://doi.org/10.1016/j.cie.2014.08.018
24. P. Plantard, H.P.H. Shum, A.S. Le Pierres, F. Multon, Validation of an ergonomic assessment method using kinect data in real workplace conditions, Appl. Ergon. **65**, 562 (2017).
25. A.M. Coruzzolo, F. Loll, N. Amicosante, H. Kuma, P. Thupaki, S. Agarwal, Comparing semiautomatic rapid upper limb assessments (rula): Azure kinect versus rgb-based machine vision algorithm, Physical Ergonomics and Human Factors **63**, 54 (2022).
26. A.A. Klein, A.L.C. Legey, A.A. Motter, E.S. Castro, M.L.L.R. Okimoto, Comparative study of rula evaluations using kinebot software, DAT Journal **7**, 161 (2022).
27. P.C. Lin, Y.J. Chen, W.S. Chen, Y.J. Lee, Automatic real-time occupational posture evaluation and select corresponding ergonomic assessments, Scientific Reports **12**, 2139 (2022).
28. D. Kee, Participatory ergonomic interventions for improving agricultural work environment: A case study in a farming organization of korea, Applied Sciences **12**, 2263 (2022).
29. T. Chatzis, D. Konstantinidis, K. Dimitropoulos, Automatic ergonomic risk assessment using a variational deep network architecture, Sensors **22**, 6051 (2022).
30. L. Singh, P. Kumar, S.K. Lohan, Development of a real-time work-related postural risk assessment system of farm workers using a sensor-based artificial intelligence approach, Journal of Field Robotics (2023).
31. R.. Arízaga, Agente inteligente para analizar los desordenes musculo esqueléticos y la evaluación ergonómica a trabajadores home office mediante redes neuronales, Journal of Interesting Articles (2020).
32. Sánchez, Evaluación de la carga física postural: ¿owas, rula o reba?, Journal of Interesting Articles (2017).
33. R. Ricardo, Enfermedades ergonómicas., Journal of Interesting Articles (2020).
34. Acuña, Desarrollo de un sistema autónomo con inteligencia artificial para el monitoreo continuo de riesgos posturales en tiempo real en minería., Journal of Interesting Articles (2019).