

PAPER

Implementing a Risk Assessment System of Electric Welders' Muscle Injuries for Working Posture Detection with AI Technology

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ABSTRACT

Maintaining health and safety is essential for workers' quality of life, and thus, this has become one of the main priorities for industrial enterprises. Electric welders want required safety precautions to be implemented during work in industries with safety risks, especially muscle injuries. This challenge needs to be addressed by the safety officer, who should suggest a way to decrease the risk for workers. However, traditional assessment based on human evaluation and the need for expertise and accuracy in risk assessment have produced muscle injuries. Thus, using artificial intelligence (AI) technology to mitigate risk assessment is cost-effective and accurate. This study proposed a risk assessment system for muscle injuries (RASMI) with AI technology to assess electric welder postures with rapid entire body assessment (REBA) standards to identify the cause of muscle injuries and to warn electric welders when their pose may be a risk. The findings showed that the system can effectively and precisely evaluate the risk assessment of electric welders' muscle injuries. Additional results showed that they perceive using AI technology to enhance wellness positively in terms of working with warnings for posture adjustment or behavior that can significantly affect an operator's long-term health and well-being.

KEYWORDS

machine learning (ML), rapid entire body assessment (REBA), risk assessment, ergonomics

1 BACKGROUND AND MOTIVATION

A welder is a skilled tradesperson specializing in joining materials, usually metals. Welding involves the application of heat to melt and fuse the materials, often adding a filler material to create a strong joint when the melted materials cool and solidify. Welding is a crucial process in the construction industry. The construction business segment is growing and in great demand, especially in cities or areas with

Ruengdech, C., Howimanporn, S., Intarakumthornchai, T., Chookaew, S. (2024). Implementing a Risk Assessment System of Electric Welders' Muscle Injuries for Working Posture Detection with AI Technology. *International Journal of Online and Biomedical Engineering (iJOE)*, 20(4), pp. 84–95. <https://doi.org/10.3991/ijoe.v20i04.46465>

Article submitted 2023-11-03. Revision uploaded 2023-12-14. Final acceptance 2023-12-14.

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department stores, bus stations, and transportation connections, such as subways or boats. Thus, the number of electric welders is increasing every year. Structural steel components are essential in generating the structure of a critical residential house, and a welder is a necessary part of building the house when it comes to the steel components. Alternatively, make a ready-made wall because it requires skill to work.

In their daily work, welders must often stand or maintain the same posture, and it takes a long time to weld materials, resulting in fatigue. Moreover, welders sustain muscle injuries and must take a break from work to heal, which causes a loss of income for them.

Many studies addressing the utilization of machine learning (ML) algorithms have assisted in solving problems in various engineering fields based on ergonomics [1]. For example, ML techniques prevent work-related musculoskeletal disorders during work [2–3]. In addition, using ML techniques for primary prevention is cost-effective when it comes to mitigating the risk of debilitating musculoskeletal diseases [4]. Some studies have already proposed activities using artificial intelligence (AI) technologies to evaluate ergonomic risk assessment methods [5]. Using ergonomic principles can improve a welding worker's posture and task, reducing exposure to risk factors and increasing productivity. A simple workstation adjustment or the use of different tools can significantly impact an operator's long-term health and well-being.

Rapid entire body assessment (REBA) is a postural analysis tool sensitive to unpredictable working postures in the health care and service industries [6]. It systematically evaluates the musculoskeletal system's upper and lower parts for biomechanical and musculoskeletal disorder risks associated with the considered working task [7]. In addition, applying REBA to evaluate ergonomic risks among standing machine operators and related risk factors will help managers and researchers better understand working conditions [8]. The main factors causing muscle injuries may be welders' awkward body postures, such as outreached arms, an awkward position of the neck and head, kneeling or squatting, a long duration of tasks, and using continuous force [9].

This study proposes using AI risk assessment of musculoskeletal systems vulnerable to muscle injuries during welding tasks performed by electric welders. Image processing is an ML method applied to aid in the risk assessment of muscle injuries based on REBA. In this vein, the study addresses the following research questions:

RQ1: Can the RASMI proposed in this study provide an accurate assessment?

RQ2: How do electric welders perceive using AI technology?

2 RELATED WORK

2.1 The risk of muscle injuries among electric welders

Thailand has a significant manufacturing sector, particularly in the automotive, electronics, and construction fields. Therefore, welding technologies are popular and demand workers from the country and neighboring countries. Muscle injuries are the most frequent cause of injury for workers, especially in the construction industry, who have a significant risk of injury [10]. Electric welders often work in positions that strain the joints and muscles when welding while being forced to

adopt awkward postures. Therefore, they have muscle injuries or disorders of the muscles, tendons, ligaments, joints, or related soft tissue, including a sprain, strain, or inflammation, that may be caused or aggravated at work.

A report on accidents and illnesses at work in Thailand in 2018–2022 found that a high-frequency cause is musculoskeletal injuries occurring because of work [11]. This is the leading cause of workers' absences, and workers' sick leave rates are increasing. To cope with this challenge, the prevention of musculoskeletal injuries is essential. Therefore, safety officers must provide recommendations and reminders of mitigation strategies to bring about a decrease in worker risk.

2.2 Machine learning

Machine learning is a branch of the AI system that predicts task output values from given input data [12]. An ML system engages in the type of experiential learning associated with human intelligence while also being able to learn and improve its analyses using computational algorithms [12–16]. ML can be applied in ergonomics, which focuses on improving human comfort, safety, and performance. Many studies have proposed the integration of ergonomic risk assessment scores using computer vision and ML approaches concerned with machines' understanding of image data [17–18]. Computer vision can be used to process, load, transform, and manipulate images to create an ideal dataset for the AI algorithm. This study integrates ML techniques with image processing methodologies that leverage the capabilities of ML algorithms to enhance, automate, or optimize image processing tasks.

Machine learning models can be trained to predict potential ergonomic risks or hazards based on historical data by analyzing patterns and correlations. These models can help to proactively identify potential issues before they lead to injuries. This study used ML and computer vision to detect posture and assess the risk of muscle injuries in real-time. Thus, to calculate the confusion matrix, accuracy, precision, recall, and F1 score of the model, the following formulas were used [19]:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \quad (1)$$

$$\text{Precision} = \frac{\text{True Positive (TP)}}{\text{True Positives (TP) + False Positive (FP)}} \quad (2)$$

$$\text{Recall} = \frac{\text{True Positive (TP)}}{\text{True Positives (TP) + False Negative (FN)}} \quad (3)$$

$$\text{F1 Score} = \frac{2 * \text{True Positive}}{2 * \text{True Positive (TP) + False Positive (FP) + False Negative (FN)}} \quad (4)$$

2.3 Ergonomics assessment with REBA

Rapid entire body assessment evaluates the risk of musculoskeletal disorders associated with specific tasks within each job [20]. Thus, multiple studies have proposed using REBA to improve workers' muscle injuries in many job fields, especially

in the industrial sector [21–22]. REBA assessment determines the postural angles of six body parts: the neck, trunk, legs, shoulders, arms, and wrists. Moreover, it uses other data, such as determining the load, force, and duration required to perform the task. It then delivers an overall score considering all body parts. The daily work of an electric welder, which requires standing or maintaining the same posture for a long time, often causes muscle aches or injuries to the back muscles, as shown in Figure 1.

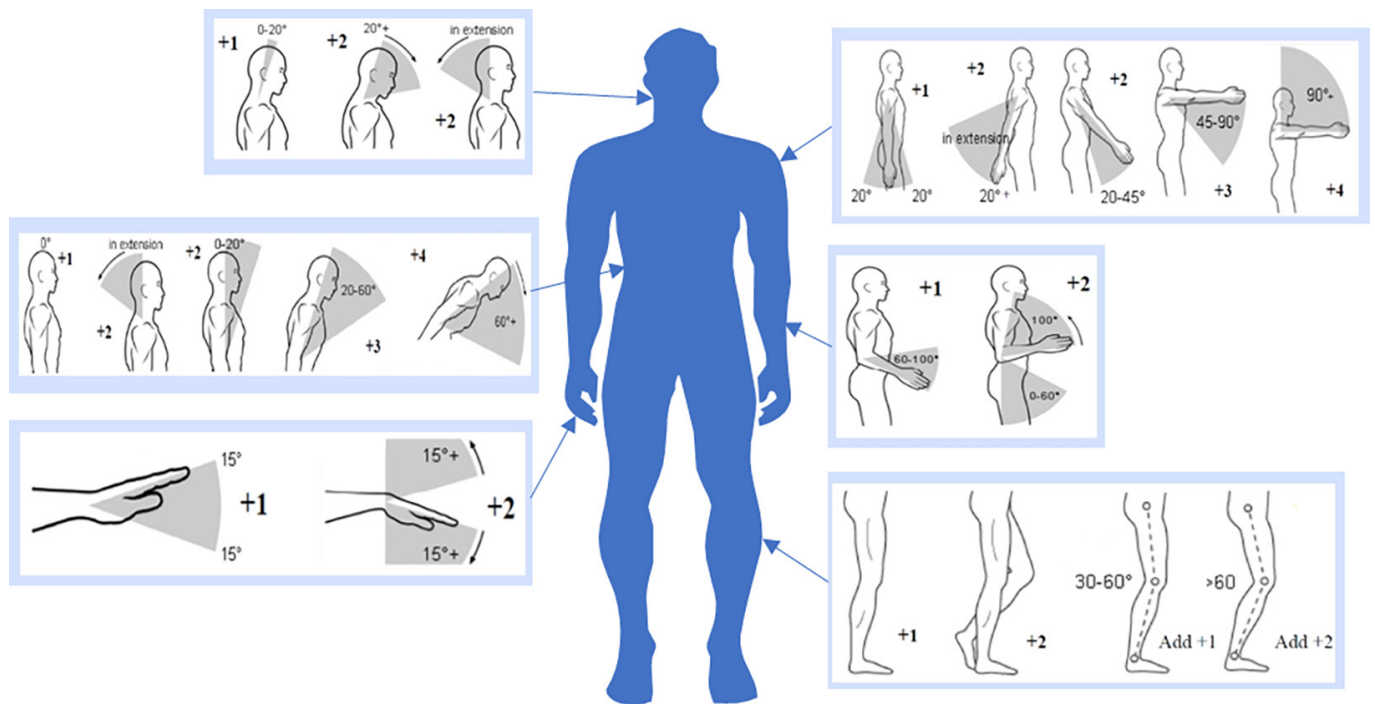


Fig. 1. Calculation of working posture based on REBA criteria [6]

3 DEVELOPMENT OF A RASMI

In this study, we designed and developed a RASMI for electric welders. Using images of the poses of electric welders that evaluate the angle of movement can identify the risk of muscle injuries based on REBA standards. First, we used the machine vision technique with OpenCV-Python and Media Pipe, which are application programs, to develop our system.

Google developed Media Pipe, a cross-platform library that provides ML solutions to support multimodal graphs for speeding up processing. Different calculators run in separate threads. Media Pipe estimates 33 key points of the body called pose landmarks, including x, y, and z coordinates. OpenCV (Open-Source Computer Vision Library) in Python is a computer vision library that is widely used for image analysis, image processing, detection, and recognition [23–24].

Figure 2 shows the overall development of the system, which includes the data input phase for the ML process to create algorithms. The algorithms require a large amount of data to learn and predict highly accurate results to ensure that the images are well processed. After that, the testing phase uses the webcam to evaluate the electric welder and receive feedback in the data output phase.

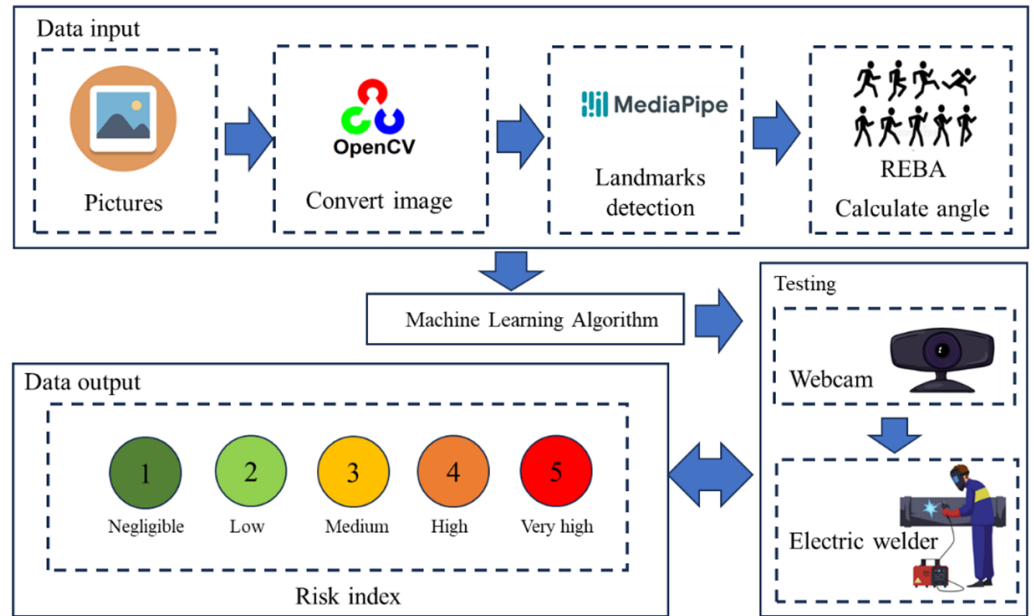


Fig. 2. Overview of the system

Standing and sitting while welding depend on several factors, including the nature of the welding job, the task’s duration, and the welder’s personal preferences. Some welding tasks may involve standing and sitting, allowing the welder to adapt to different aspects of the job. It is crucial to prioritize ergonomics, safety, and the overall well-being of the welder when choosing a welding position. Figure 3 shows an example picture used in the training process. We used images of electric welders to train an ML model on standing and sitting to estimate posture.

Moreover, Figure 4 shows the pose landmark model tracking body location; this represents the approximate location to evaluate the angle of body movement. After that, we followed a stepwise methodology of REBA assessment criteria to calculate the data on the working posture angle.



Fig. 3. Posture images of welders in the training data: (a) standing posture (b) sitting posture

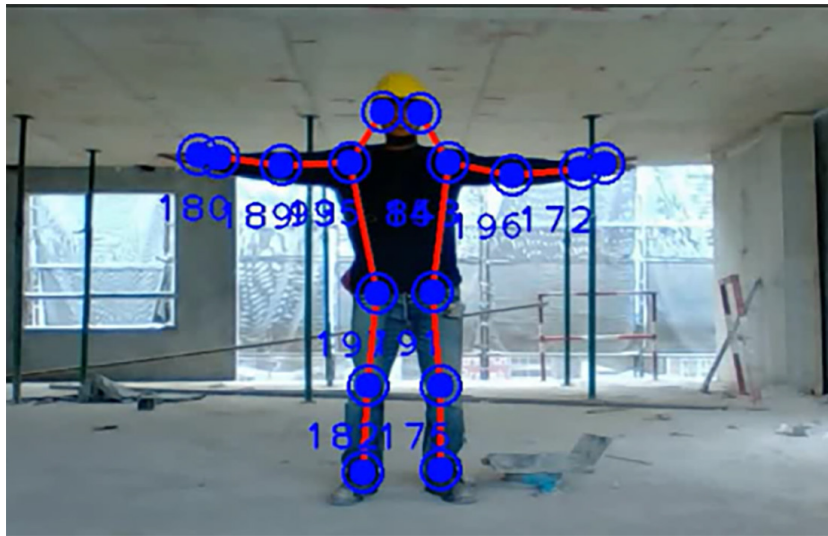


Fig. 4. Pose body landmarks

The REBA score represents the level of muscle injury risk; we use the REBA worksheet to calculate the angle measurement and give the score, observing the force load and movements' repetitiveness and the postural changes' frequency [1]. The results show the total score, with the minimum score of 1 and the maximum score of 15. At the same time, the risk index has five risk levels, from negligible risk to very high risk. Meanwhile, it shows a five-risk index, including 1 to 5. Each index shows action suggestions to improve working behavior (refer to Table 1). Figure 5 shows the details of the system output after detecting posture. It displays a real-time safety symbol color based on the risk index, scored as follows: level 1 = green, level 2 = lime, level 3 = yellow, level 4 = orange, and level 5 = red.

Table 1. Risk index and action suggestions based on REBA scores

REBA		Risk Index	Action Suggestions
Scores	Risk Level		
1	Negligible risk	1	No necessary changes
2-3	Low risk	2	Changes may be needed
4-7	Medium risk	3	Further investigation and change
8-10	High risk	4	Investigate and implement change soon
> 11	Very high risk	5	Implement change now

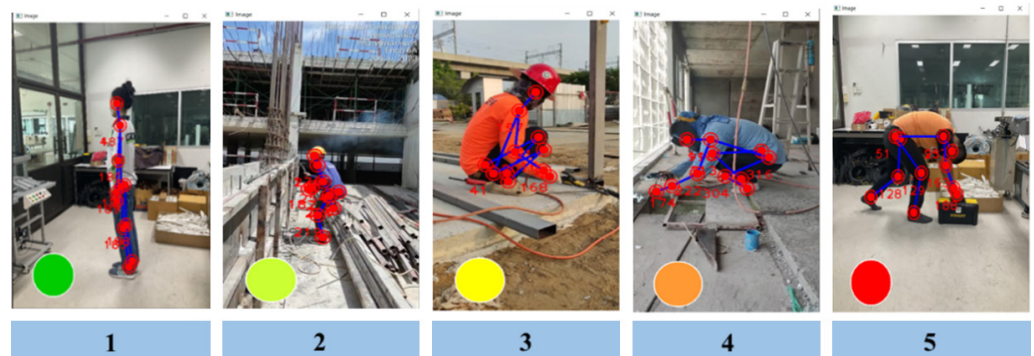


Fig. 5. Risk index display of the RASMI

4 METHODOLOGY

4.1 Participants

The participants in this study were electric welders recruited from a construction company in Bangkok, Thailand. 24 workers from three countries—Thailand, Cambodia, and Myanmar—volunteered to participate in the experimental research to receive a RASMI assessment. Most of the welders were interested in and excited about using AI technology. The demographics of the participants are shown in Table 2.

Table 2. Demographics of the participants

Demographics	Frequency	Percentage (%)	
Gender	Male	23	96.83
	Female	1	4.17
Age (years)	20–29	8	33.33
	30–39	13	54.16
	40–49	3	12.50
Nationality	Thai	8	33.33
	Cambodian	9	37.50
	Burmese	7	29.17
Education level	Primary	20	83.33
	Secondary	4	16.67
Work experiences	Under 1 year	9	37.50
	1–5 years	11	45.83
	6–10 years	3	12.50
	Over 10 years	1	4.17
Training experiences	Yes	3	12.50
	No	21	87.50
Working time	Under 6 hours	14	58.33
	6–8 hours	10	41.67
Muscle injury frequency	0	4	16.66
	1–5/month	14	58.33
	6–10/month	4	16.66
	11–15/month	2	8.33

4.2 Data collection

We aimed to gather accurate data for this study. To accomplish this, we collected data from electric welders in their workplaces. We set up the equipment for this study, including a laptop computer and webcam, as shown in Figure 6. After participants used RASMI to evaluate their posture during welding, they completed the perception questionnaire. Since some participants were workers from neighboring countries, they needed help reading the questionnaire in Thai. However, they understood the conversation in Thai.



Fig. 6. Equipment setup for data collection

5 RESULTS

5.1 RQ1: Can the RASMI proposed in this study make an accurate assessment?

During the process, we used 1,230 pictures of electric welders to train the ML model. ML accuracy, precision, and recall are metrics for evaluating models. The results show the accuracy of the system that is used in evaluating the posture welding of workers and show the percentage of correct assessments made by the model. We used short videos to test the trained model and found that the confusion matrix is true positive (TP) = 1149, true negative (TN) = 0, false positive (FP) = 81, and false negative (FN) = 0. It was a decent classifier, considering the larger number of true positive and true negative values. The accuracy reached 93% (see Figure 7). In addition, the model of the system has a precision of 0.934; in other words, when it assesses posture for a risk of muscle injury, it is correct in 93% of cases. It has a precision of 0.934 (TP = 1,149, FP = 81); in other words, it gives a correct assessment in 93% of cases (see Figure 7). The recall was 1.00 (TP = 1,149, FN = 0), and the F1 score was 0.966. This means the RASMI is doing a great job of risk assessment.

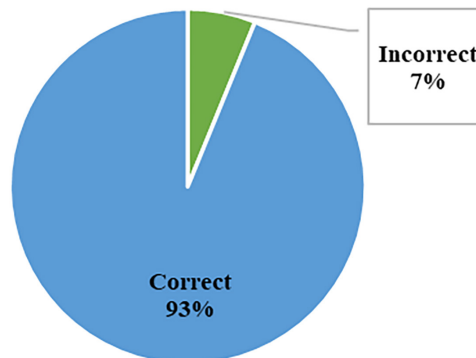


Fig. 7. Accuracy evaluation of the system

5.2 RQ2: How do electric welders perceive using AI technology?

To investigate the second research question, we adapted the questionnaire to evaluate the electric welders' perceptions of AI implementation [25]. In analyzing the data, both qualitative and quantitative approaches were employed. The descriptive analysis revealed their perceptions. The three dimensions include perceptions of AI, advantages of using AI, and application of AI in the risk assessment of muscle injuries. Table 3 shows that electric welders have a positive perception of RASMI as an AI technology tool to help them. In addition, it can be easy to assume that they are ready to encounter AI in their work because they perceive the advantages of using AI, which can impact their everyday lives.

Table 3. Electric welders' perception of using AI technology

Item	Mean	SD
Perceptions of AI		
1. AI can represent experts in assessing risk.	4.652	0.698
2. AI's abilities are superior to human experience.	4.565	0.712
3. AI could replace me in my job.	4.870	0.448
4. I have high hopes for AI applications in this context.	4.783	0.507
5. I have a positive perception of using AI in risk assessment.	4.739	0.606
Advantages of using AI		
6. AI can speed up the process of risk assessment.	4.783	0.507
7. AI has no space–time constraint.	4.826	0.480
8. AI can help reduce the number of assessment errors.	4.696	0.687
9. AI has no emotional exhaustion or physical limitations.	4.783	0.507
10. AI can deliver risk assessment in real time.	4.739	0.735
Application of AI in risk assessment of muscle injuries		
11. AI is easy to use.	4.870	0.448
12. AI was developed by a specialist with little clinical experience.	4.826	0.480
13. AI can accurately assess the risk of muscle injury.	4.913	0.282
14. AI is flexible enough to be applied to every electric welder.	4.826	0.480
15. AI is used to provide suggestions in unexpected situations.	4.739	0.606

Notes: 1.00–1.50 = strongly disagree, 1.51–2.00 = disagree, 2.51–3.50 = moderately agree, 3.51–4.50 = agree, 4.51–5.00 = strongly agree.

6 CONCLUSION

This study proposed a RASMI with AI technology to assess electric welder postures with REBA standards to identify the cause of muscle injuries and to warn electric welders when their pose may be a risk. The findings show that the system can effectively and precisely evaluate the risk assessment of electric welders' muscle injuries. Additional results show that welders positively perceive using AI technology to enhance wellness when working with warnings for posture adjustment or behavior that can significantly impact an operator's long-term health and well-being.

The everyday work of an electric welder, which requires standing or holding the same posture for a long time, often causes muscle aches or injuries. This issue can be prevented by refraining from repeating the same gestures over a lengthy period of time. In future studies, we will consider different types of workers' activities and use many data types to evaluate the accuracy of AI algorithms and improve the user interface with the system.

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