SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V13I3P122

Volume 13 Issue 3, 282-291, March 2026


*Original Article*

# A Raspberry Pi-based Computer Vision Framework for Automatic Modified-REBA Ergonomic Analysis

Agus Prijono[1], Aan Darmawan Hangkawidjaja[1], R Ratnadewi[1*], Winda Halim[1], Dasapta Erwin Irawan[2]

[1]*Universitas Kristen Maranatha, Bandung, West Java, Indonesia.*
[2]*Institut Teknologi Bandung, Bandung, West Java, Indonesia.*

**Corresponding Author : ratnadewi@ko2pi.org*

Received: 16 December 2025 Revised: 18 January 2026 Accepted: 24 February 2026 Published: 23 March 2026

***Abstract*** *- The purpose is to automatically evaluate workers' ergonomic positions in Micro, Small, and Medium Enterprises (MSMEs) using images or video footage. It utilizes the use of ergonomics, computer vision, and Internet of Things (IoT), as well as edge computing with a Raspberry Pi-based technology system. In this research, the methodology involves applying computer vision, mainly on the respective key points of a person's anatomical structure, in order to determine the "Modified-Rapid Entire Body Assessment" (Modified-REBA) Risk Score. The development of the system has taken place via the Python Programming Language, driven by PyQT 5. The development also initially took place through the use of multiple libraries; for example, OpenCV and MediaPipe (BlazePose), and TensorFlow Lite. As for the hardware aspect of the system development, the components that have been used are Raspberry Pi 4B+, ORBBRC 3D Camera, a 1920 x 1080 Monitor, wireless peripherals, and much more. By measuring what the Modified-REBA Risk Score was through this system, it is therefore a viable means of being able to do an Ergonomic Risk Assessment to help MSMEs develop their activities further. By measuring angles through the method of computer vision, the methodology provides a straightforward method for the evaluation of a worker's posture; however, an accurate result is best obtained through proper imaging. By adding more ergonomic factors, such as time spent and the weight of objects used by employees, improvements could be made to the current process. By utilizing the REBA (Rapid Entire Body Assessment) method as a risk assessment tool for identifying injury risks associated with the various postures used in a given task, appropriate adjustments can be made to decrease potential injury and improve employee safety. The computer vision approach for Modified-REBA development not only provides a useful addition for ergonomic assessment but also satisfies the Sustainable Development Goals (SDG), particularly for developing countries, as MSMEs provide a key contribution to their economies. This research presents a user-friendly system combining software for REBA calculations and hardware (Raspberry Pi and ORBBEC camera) to enable easy ergonomic assessments in MSMEs, allowing direct use of the device with a camera.*

***Keywords*** *- Computer-vision, Ergonomics, Modified-REBA, Raspberry-pi, MSMEs, SDGs.*

## 1. Introduction

The advancement of digital technology is a major contributor to Industry 4.0. Selecting the appropriate electronic equipment is essential for industrial processes [1]. This object detection sensor, the Orbbec Astra S camera, is the subject of this study. The computer vision system receives digital images from the camera and must process them for meaningful interpretation.

Digital images can be black and white, RGB color, spectral, or thermal [2]. In this study, RGB color images will be used as system inputs. Orbbec Astra S and Orbbec Persee [3, 4] are included in passive vision sensors, because these sensors receive input from natural light reflected on the detected object.

Some examples that have used various sensors are: computer vision in the field of agriculture [5], IMU sensors in the manufacturing industry [6]. Next, the RGB digital image data will be processed with image processing algorithms and artificial intelligence.

This study uses digital images to detect working people. When the camera captures an image, the computer receives it as a wide x high data format, but cannot initially interpret the content. An inference pipeline, using Non-Maximum Suppression (NMS), detects human objects and tracks their pose by predicting key point coordinates. Bazarevsky et al. used BlazePose, a convolutional neural network designed for real-time human pose estimation on mobile devices. During inference, the network generates 33 key points for one human body and runs at more than 30 frames per second (see Figure 1) [7]. In Manghisi's research, 25 key points were generated with the Kinect V2 sensor [8], and in Li's research, et al. used 17 key points [9].

In Indonesia's small industries, Manual Material Handling (MMH) is prevalent, but it carries significant work risks, especially with regard to Musculoskeletal Disorders (MSDs). For example, in America, 79% of cases are caused by MSDs, which raises healthcare costs, increases absenteeism, and decreases productivity [8, 9]. NIOSH states that a number of factors, such as unnatural posture, repetitive movement, excessive load, and static posture, can increase the risk of injury in MMH [12]. If these risk factors continue to recur, it can result in fatigue and discomfort at work and further cause injuries.

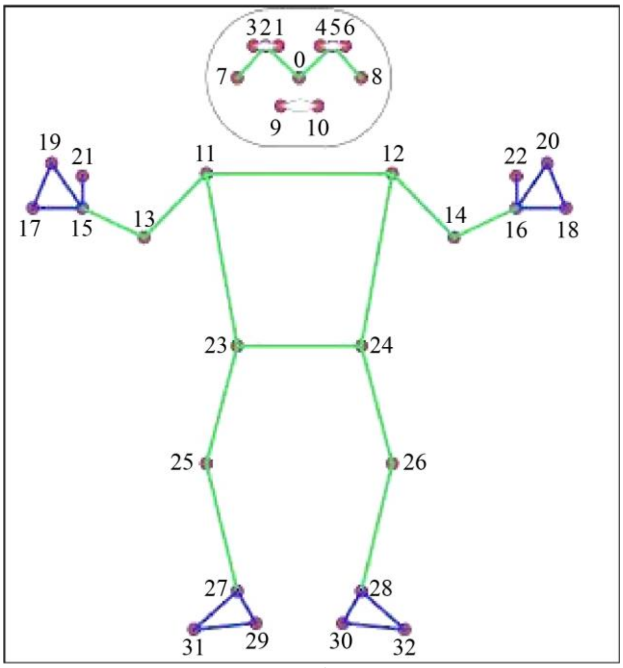


**Fig. 1 Pose 33 key points for the human body [7]**

The levels of hazard control for injury prevention are ranked as follows: Elimination, Substitution, Engineering Controls, Administrative Controls, and finally, Personal Protective Equipment (PPE) [13]. Elimination involves the removal of the hazard, for instance, carrying heavy loads or using sharp objects, while Substitution involves replacing the hazard with a safer one. These two levels of control can be very effective, especially when designing new equipment or processes. Engineering Controls involve changing work equipment or environment, while Administrative Controls, like training, involve the management level. Lastly, Personal Protective Equipment (PPE) will assist in reducing the hazards associated with exposure to workplace hazards. It is generally a good idea to do a simple and quick assessment of the hazard levels for workers before implementing control measures. The recommended methods to conduct a risk assessment of workers are to use either the OVAKO Working Posture Analysis System (OWAS), RULA (the Rapid Upper Limb Assessment), or REBA (the Rapid Entire Body Assessment). The assessments are conducted using tables and pictures. Each assessment has many advantages and disadvantages associated with it [14]. OWAS assesses poor work postures and involves two processes that include looking at what a worker is doing (the observation stage) and then analyzing the information objectively and redesigning [15]. RULA (Rapid Upper Limb Assessment) is a survey used to help evaluate the safety of workers extending from their upper backs to their hands; it does not include any equipment needed for determining neck position and upper body position [16]. REBA is a postural analysis tool that helps in determining work postures among health workers and other service industries [17]. The OWAS and REBA methods identify the entire body, while the RULA method only focuses on the upper body [14].

Several studies have been conducted to observe the risk of body posture while working, among them was conducted by [18], who studied the working conditions of surgeons. Surgeons face over 80% risk of injury due to poor ergonomics in the operating room. Long surgeries require awkward or static positions, leading to discomfort that is often ignored, affecting productivity and potentially threatening careers. Many surgeons are unaware of guidelines to improve comfort. Modifications in the operating room can reduce risks, and exercise programs led by trained therapists can help improve musculoskeletal health [18].

In the research [9], Convolutional Neural Network (CNN) and Rapid Upper Limb Assessment (RULA) algorithms were used to assess real-time risks in work related to musculoskeletal disorders (MSD). The data is the pose of the body posture while in the laboratory. The method used for RULA input assessment uses body part angles (such as upper arm, lower arm, wrist, neck, and upper trunk), muscle use, and external load [9].

The use of the Dynamic Time Warping modification method and RULA to observe different time action sequences in physiological functions is divided into three parts, namely: 1) measuring the level of joint mobility, 2) investigating abnormalities in upper body movements, and 3) detecting abnormal walking styles for the lower body [19].

The Ergo Explorer software is an innovative type of technology created for the purpose of extracting digital media-based information (such as video) and providing users with the ability to conduct a thorough analysis of the data collected [20]. Ergo Sentinel also uses digital input to monitor the risk factors associated with developing a musculoskeletal disorder due to improper posture, which can occur as a result of poor ergonomics when completing daily tasks [8]. The goal of the research project being conducted is to create a tool capable of automatically conducting a work activity analysis for micro, small, and medium-scale enterprises (MSMEs), using image data to obtain information about the worker's approach to completing the task.

There is still a big gap in the development of an automated, real-time, and reasonably priced posture-risk assessment system made especially for MSMEs involved in manual material handling tasks, despite earlier research showing that combining computer vision and ergonomic assessment tools is feasible. The majority of current methods rely on costly sensor technologies, controlled laboratory datasets, or semi-manual RULA/REBA scoring processes, which restricts their applicability in small industrial settings. Additionally, not many studies have looked at how RGB-based passive vision sensors may be integrated with pose-estimation algorithms to automatically create ergonomic risk ratings in Indonesian MSMEs under actual operating situations.

Therefore, the lack of an automated and easily available system that can analyze worker posture during MMH operations and convert pose-estimation outputs into ergonomic risk assessments appropriate for small-scale industrial environments is the main issue this study attempts to address. This study intends to close this gap by creating and testing a computer-vision-based application that automatically detects human posture, extracts key-point coordinates, and supports objective ergonomic risk analysis using RGB picture data from the Orbbec Astra S sensor. This study enhances workplace safety and lowers the risk of musculoskeletal illnesses while advancing the practical deployment of Industry 4.0 in MSMEs by bridging the gap between formal ergonomic assessment and real-time pose estimate.

## 2. Literature Review

### *2.1. Rapid Entire Body Assessment (REBA)*

The Rapid Entire Body Assessment (REBA) is an ergonomics assessment tool that evaluates how various work positions affect the risk of developing musculoskeletal disorders. In order to determine what intervention is needed, the different areas of the body - neck, torso, legs, arms, feet, hands - are assigned a score based on their position, frequency of occurrence, force exerted, and method of holding something.

REBA has been validated in several studies that show the effectiveness of using REBA in both industrial and health care environments. In one study of the clothing industry, an obvious connection was found between awkward postures and the occurrence of discomfort in the musculoskeletal system, thus confirming the ability of REBA to accurately assess the risk of developing musculoskeletal disorders. Other research studies involving the use of REBA in the assessment of postural risks among agricultural workers also prove the versatility of the method.

In the comparative ergonomic study, REBA was compared to other methods, such as RULA [21] and OWAS, and the results showed that REBA is more detailed when considering the entire body when moving and under variable loads. The authors highlighted the combination of REBA and digital video analysis to increase accuracy when using observation methods. Within the Industry 4.0 paradigm as well as human-centered design, REBA is being increasingly integrated with wearables and machine learning algorithms to enable automated posture identification and risk analysis. This is yet another indication of its relevance to modern ergonomics studies.

REBA can be calculated with pen and paper, assessing body parts such as the spine, neck, legs, arms, forearms, and wrists. The full assessment and table can be seen in Figure 2 [17, 22].

Body posture assessment based on sensitivity and its analysis has also been carried out by [23], which is useful in industry to redesign REBA. With screenshots and combined with REBA, worker safety and productivity are more optimal [24]. Model ini dapat pula digunakan untuk gait recognition [25].

The combination of using an open pose and an RGB-D camera to identify body anatomy in several positions, namely, standing and sitting [26]. A combination of machine learning and REBA to improve construction worker safety [27]. The use of REBA based on fuzzy and Bayesian networks is also used [28].

Comparison of the performance of using Kinect and Openpose on the REBA semi-automatic system proves that Openpose performs better [29]. Currently, the use of REBA combined with deep learning [30] and 3D models is starting to be developed [31].

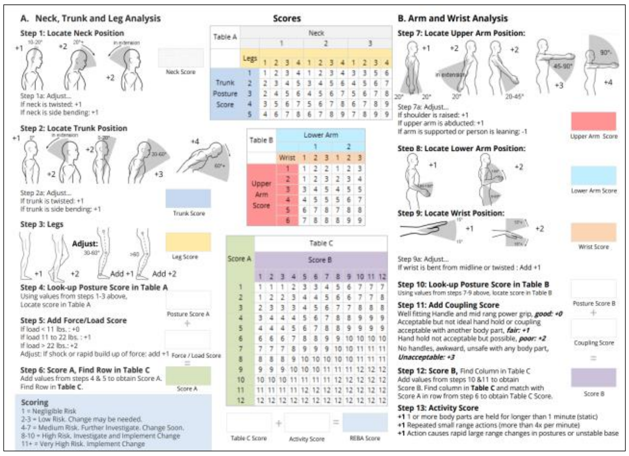


**Fig. 2 Rapid Entire Body Assessment (REBA) [22]**

### *2.2. Computer Vision*

Computer vision is a branch of Artificial Intelligence (AI) that aims to enable computers to acquire, process, analyze, and understand visual information from their surroundings. Unlike traditional image processing, which focuses only on manipulating or improving image quality, computer vision emphasizes the interpretation of meaning from visual data [32]. Computer vision systems do not just “see” images as a collection of pixels, but are also capable of recognizing patterns, identifying objects, and extracting relevant information to support automated decision-making. Technically, computer vision works through several main stages. The process begins with image acquisition using devices such as RGB cameras, depth cameras, or thermal sensors. The visual data obtained then goes through a pre-processing stage, such as noise reduction, normalization, or color space conversion, to improve the quality of the information. Next, important features of the image are extracted using specific techniques, either based on classical methods (e.g., edge detection or geometric transformation) or machine learning and deep learning approaches. In the final stage, artificial intelligence models perform inference to generate outputs such as object classification, position detection, image segmentation, or human pose estimation.

Significant developments in computer vision occurred with the advent of Convolutional Neural Networks (CNNs) and other deep learning architectures capable of automatically learning feature representations from large amounts of data. This approach improves the accuracy of systems in various tasks such as image classification, object detection, image segmentation, and human pose estimation. With these capabilities, computer vision has become a core technology in various intelligent systems, including autonomous vehicles, facial recognition-based security systems, product quality inspection in the manufacturing industry, and even work posture analysis to prevent musculoskeletal disorders.

In the context of modern industry and the transformation towards Industry 4.0, computer vision plays a major role in data-driven automation and monitoring. Its integration with the Internet of Things (IoT), edge computing, and artificial intelligence-based analytics enables real-time production processes and workplace safety monitoring. Thus, computer vision not only improves operational efficiency but also supports more accurate and evidence-based decision-making across various industrial and service sectors.

### *2.3. Image Processing*

Image processing is a field in computer engineering and electronics that focuses on manipulating and analyzing digital images to improve visual quality or extract specific information [33, 34]. Conceptually, image processing operates at the pixel level, where each image is represented as a two-dimensional matrix consisting of light intensity values or color components (e.g., RGB). The main purpose of image processing is not always to understand the meaning of objects in an image, but to improve, transform, or prepare images for further analysis by more complex systems such as computer vision or machine learning.

In practice, image processing includes various basic techniques such as color space conversion, contrast enhancement, noise reduction using spatial filters (e.g., Gaussian or median filters), and edge detection using operators such as Sobel or Canny. These processes aim to improve the quality of visual information contained in images so that important features become clearer and better defined. In addition, geometric transformations such as rotation, translation, and scaling are also included in the scope of image processing, especially to adjust images to specific analysis requirements.

Image processing also includes segmentation techniques, which are the process of separating objects from the background based on differences in intensity, color, or texture. Segmentation is an important step in many applications because it allows the system to focus its analysis on only the relevant areas. Segmentation methods can be simple, such as thresholding, or more complex, such as watershed or k-means-based clustering. At this stage, images are often converted into binary or mask forms to facilitate further analysis.

In the context of industry and research, image processing plays a strategic role as the initial stage in the intelligent visual system pipeline. Before visual data is processed by artificial intelligence models, images need to go through a pre-processing stage to reduce noise and improve feature quality. Thus, image processing serves as a technical foundation that ensures that the visual data used in analytical systems is of optimal quality, thereby improving the accuracy and reliability of the overall analysis results.

## 3. Methodology

### *3.1. Method of 3 Key Points Angle On Modified Reba*

The method of calculating angles from 3 key points is used to assess each body segment, as can be seen in Figure 2. The angle at point B is calculated against points A and C that form lines AB and CB (see Figure 3).

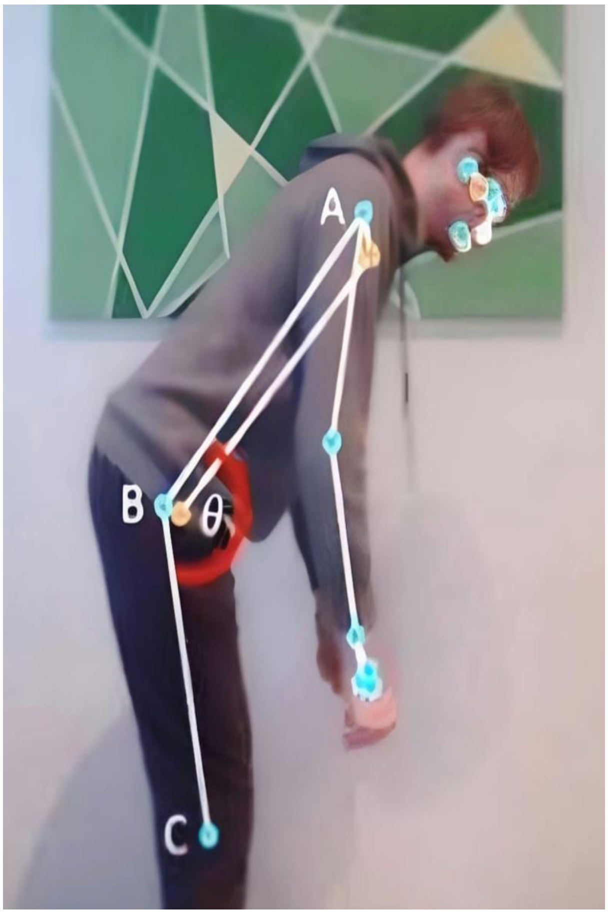


**Fig. 3 Determination of key points for angle calculation [35]**

In the design here, the calculation of six angle values is used, namely neck, trunk, legs, upper arm, lower arm, and wrist.

The neck calculation is taken at: (mid 7-8), (mid 11-12), (mid 23-24); the trunk calculation is taken at: (mid 25-26), (mid 23-24), (mid 11-12); the legs calculation is taken at: (mid 23-24), (mid 25-26), (mid 27-28), the upper arm calculation is taken at: (mid 23-24), (mid 11-12), (mid 13-14), the lower arm calculation is taken at: (mid 15-16), (mid 13-14), (mid 11-12); and the wrist calculation is taken at: (mid 13-14), (mid 15-16), (mid 17-18) (see Figure 4).

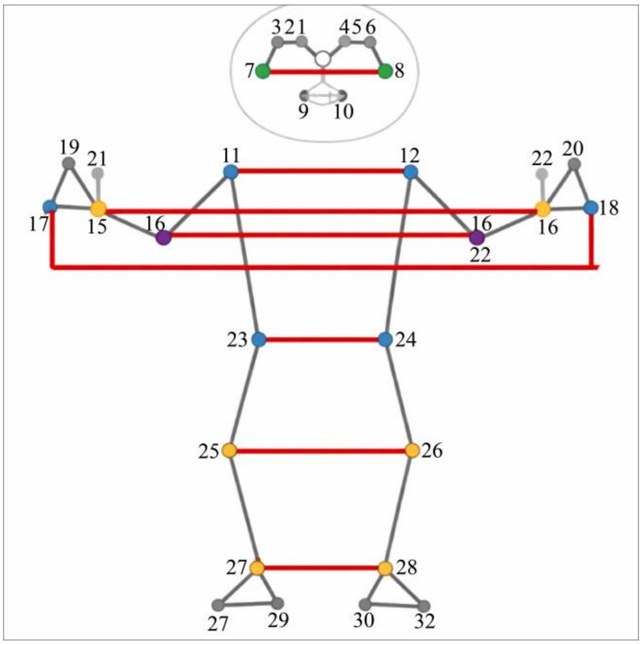

**Fig. 4 Determination of key points for calculation**

### *3.2. Application System Design*

The application is designed based on the SBC Raspberry Pi so that it can be used portably and efficiently. From the Figure 5 system block diagram, inputs can be in the form of real-time video captures (live), an image file, or a video file. The captured images from the webcam or downloaded files via OpenCV will be read per frame, then the key point search process is performed using a library from MediaPipe and TensorFlow. Based on the key points determined, the calculation of the Modified-REBA is done as per the pose. Additionally, the adjusted parameter value is used to achieve the final Modified-REBA score.

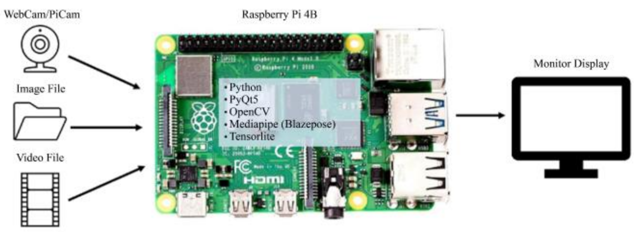


**Fig. 5 Block diagram system**

## 4. Results and Discussion

### *4.1. Software*

The software is coded in Python, which was chosen for its flexibility and readability. It uses the PyQt5 library for building high-quality graphical user interfaces. OpenCV is used for image and video processing in real-time, while MediaPipe, in collaboration with its BlazePose model, is responsible for the real-time tracking of human poses. TensorLite also supports machine learning capabilities for mobile devices.

Figure 6 shows the process flowchart for the software application. The software development has been done using Python 3.10, with the help of PyQt5 for designing the interface. The interface has two image/video display options for images/videos with keypoints (including the REBA value computed from the pose keypoints) and image/video keypoints displayed on a white screen. The interface also has the option to input the REBA adjustment parameters, as shown in Figure 2.

The final REBA score can be obtained by pressing the 'Process' button. The REBA score counter interface is set to a monitor resolution of 1920 x 1080. Figure 7 shows the design of the modified REBA score counter.

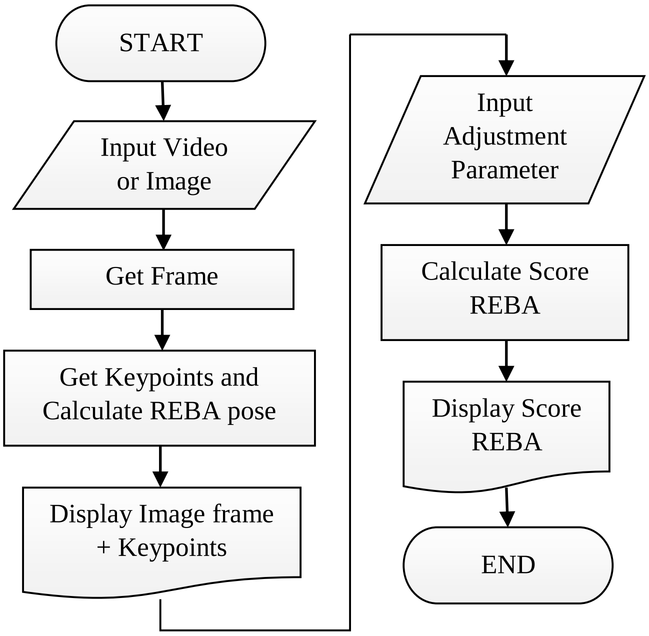


**Fig. 6 Flowchart of modified-REBA software**

**Fig. 7 Interface display of modified-REBA score counter**

### *4.2. Hardware*

For achieving the desired results, various hardware components were utilized in this experiment. At the forefront of the hardware configuration was the Raspberry Pi 4B+, which was accompanied by 4 GB of memory and a 32 GB microSD card. The Raspberry Pi ran on the Debian OS version 11, also known as "Bullseye," to ensure a stable and secure execution environment.

In addition to that, a 3D ORBBEC camera was used to capture images of a higher quality that were three-dimensional, which was necessary for the experiment. Images captured by Raspberry Pi, as well as images captured by the 3D camera, were displayed on an HD monitor that has a resolution of 1920 x 1080.

For the interaction of the system, a wireless keyboard and mouse were used. This made the interaction flexible.

Figure 8 shows a detailed illustration of the hardware setup. This is a comprehensive representation of the arrangement of the hardware in the experimental setting.

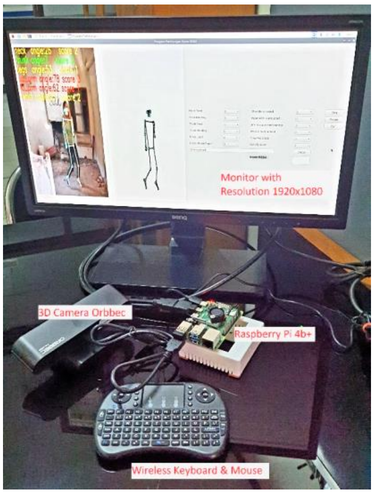


**Fig. 8 Hardware setup used in the experiment**

### *4.3. Data Analysis*

This research provides a comprehensive description of the outcome of the program execution. The data was collected through a survey of the daily activities performed by the employees of Micro, Small, and Medium Enterprises (MSMEs), which are referred to as MSMEs in Indonesia, in their factories. The sample was carefully selected to give a complete representation of the daily activities performed in these factories.

*4.3.1. Activity 1: Washing Bottles*

The definition of the first activity is shown in Figure 9, where the role played by the operators in the soy sauce manufacturing factory is evident regarding the cleaning of the bottles. The operators can efficiently perform tasks by utilizing a special stool. A series of actions is performed by the operator to clean the bottles hygienically and maintain the cleanliness required for the production line.

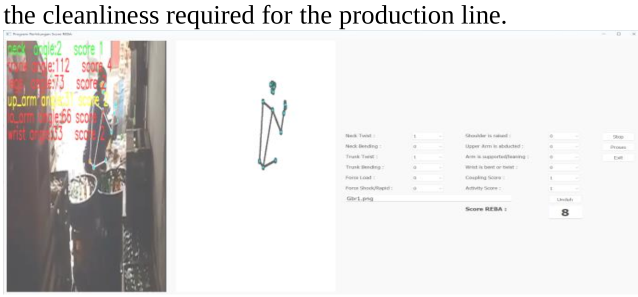


**Fig. 9 Washing bottles**

In Figure 9 above, six different angle values were measured with respect to the neck, trunk, legs, upper arm, lower arm, and wrist regions. All the angles provide critical data necessary for the analysis of the posture and overall ergonomic conditions under investigation. Using the advanced ergonomic analysis software called the Modified-REBA (Rapid Entire Body Assessment) program, the individual score for each angle is calculated. This score indicates the level of physical effort required or the ease with which the corresponding body part can move. The overall score is calculated by the program to determine the Total Modified-REBA score.

*4.3.2. Activity 2: Stirring Soy Sauce*

Activity Description: The main activity of the operator is to stir the thick soy sauce liquid in the heated furnace using a strong bamboo stirrer. The operator can sit or stand as he or she feels like. The cyclical motion of the stirrer is used to mix the liquid evenly, which is important for the quality of the soy sauce (Figure 10).


**Fig. 10 Stirring soy sauce**

*4.3.3. Activity 3: Lifting Raw Materials to the Milling Machine*

In this operation, the operator must lift a 35-kilogram drum containing soybeans to the funnel of the milling machine, which is located at the top. The operator has to do this without spilling the soybeans, which makes it possible for the soybeans to be conveyed smoothly into the machine for processing (Figure 11).


**Fig. 11 Lifting raw materials to the milling machine**

*4.3.4. Activity 4: Fetching Water*

Activity Definition: This refers to important supporting activities that enable seamless operations. These tasks that utilize water may include washing soya sauce containers and keeping the work environment clean and sanitary. Since they are structured tasks and therefore are needed in the operation as well, this type of support is vital to the long-term success of this work-supported operation (Figure 12).

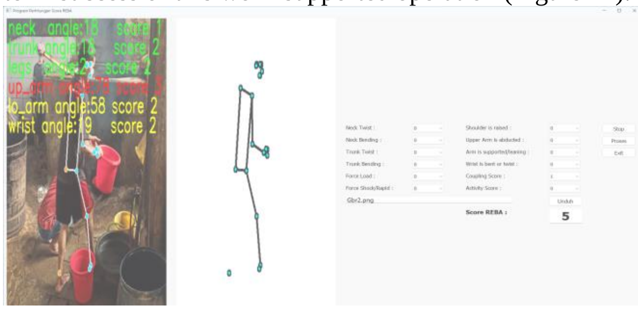


**Fig. 12 Fetching water**

#### *4.3.5. Activity 5: Lifting Raw Materials Into The Boiler Furnace*

Definition of the activity: An operator will be required to pick up and transfer a heavy bucket of raw material from a place where it is stored to the boiling furnace for further processing. It is important to understand that the weight of each bucket filled with raw material may vary greatly, but the average weight will be 20-30 kilograms (Figure 13).

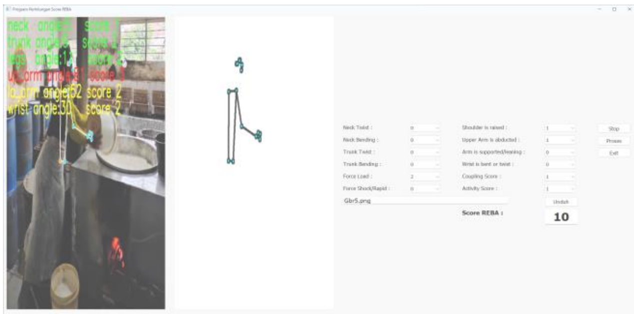


**Fig. 13 Lifting raw materials into the boiler furnace**

What follows is a comparison table. The total REBA modification scores, as shown in Table 1, were generated using software that allowed for the compilation and comparison of the REBA Employee Assessment Worksheet scores to assess employee performance, at the same time demonstrating the validity of both tools by providing a reliable means of comparison. This comparison offers a detailed look at the data from both sources.

**Table 1. Comparison between the total REBA modification score (using the program) and the total REBA score using the Employee Assessment Worksheet**

| Activity | Total Score Using Program | Total Score REBA Employee Assessment Worksheet |
|---|---|---|
| 1. Washing Bottles | 8 | 7 |
| 2. Fetching Water | 5 | 4 |
| 3. Stirring soy sauce | 9 | 10 |
| 4. Lifting Raw Materials to The Milling Machine | 11 | 11 |
| 5. Lifting Raw Materials into The Boiler Furnace | 10 | 9 |

The scores obtained from computer vision and manual methods were compared, and only one scoring resulted in identical total scores (= 11) for activity number 4. Scores differed for activities number 2, number 3, and number 5; however, they all fell within the same general risk category: creating a 'Medium Risk' for those rated between 4-7 and a 'High Risk' for those rated from 8-10. On the other hand, the total score of activity number 1 is different, as well as its risk category.

Both activity number 3, where the worker is lifting a heavy drum of soybeans, and activity number 5, where the worker is lifting a large bucket of raw material, could lead to severe injuries for the worker if improvements to posture are not made or support tools are not used. Without appropriate lifting techniques and ergonomic supports, both tasks present a risk for developing musculoskeletal disorders (e.g., strains, herniated discs, etc.) or may lead to acute injuries.

From the experiment's findings, it appears that the program successfully calculates the Modified-REBA score that will likely prove extremely useful to the REBA scoring in future MSMEs activities. Additional future research roadmap developments might include the following:

1) Expanding the areas where users can identify more subtle differences in their body positions to enhance the scoring and tracking capabilities of the program
2) Adding continuous, real-time monitoring and tracking functionality beyond one-time evaluations
3) Including more comprehensive measurements, including duration and weight, to improve the overall ergonomics of a workplace
4) Developing a feature to recommend ways an employee can improve their body posture based on the results of the REBA evaluation
5) Expanding REBA's range of activities to encompass even more complex movements.

### *4.4. Discussion on the Relevance to Sustainable Development Goals (SDGs)*

This research has strong connections to the Sustainable Development Goals (SDG) and specifically supports the advancement of the Sustainable Development Goals on Occupational Health, Availability of Low-Cost Technology Innovations, and the Empowerment of Micro, Small, and Medium Enterprises (MSME) sector.

With regard to SDG 3: Good Health and Well-being, the proposed method for using computer vision technology to assess ergonomic risks using the Modified-REBA method provides support for the prevention of Musculoskeletal Disorders (MSD) among workers in the MSME sector. This new technology will give MSMEs the ability to identify in real-time postures that are considered high-risk, thereby reducing the incidence of injury caused by excessive physical strain.

With respect to SDG 8: Decent Work and Economic Growth, this research promotes the creation of safe and secure working environments. A computer vision-based ergonomic risk assessment system provides a viable and cost-effective option for MSMEs, who typically lack access to formal occupational health services, to collect data that identifies and drives improvements to working conditions without needing to implement complicated external programs.

This research also supports SDG 9: Industry, Innovation and Infrastructure, through the utilization of low-cost Raspberry Pi devices, which can make AI-based ergonomic assessment technology accessible to small-scale industrial sectors. This study also supports the uptake of IoT and edge computing as innovations in factories via Industry 4.0, which is typically utilized by larger business entities.

This system will also provide support for SDG 12: Responsible Consumption and Production to improve efficiency in work processes and reduce the likelihood of workers developing fatigue or being injured on the job. Decreased ergonomic risk factors will result in fewer incidents of human error and disruptions to production, which contribute to creating sustainable operational capability for Micro, Small, and Medium Enterprises (MSMEs).

## 5. Conclusion

The Rapid Entire Body Assessment (REBA) allows for a quick and practical way of evaluating a worker's musculoskeletal disorder-related postural risk. Furthermore, there are several advantages to using this tool, as it allows one to determine the position of the worker that may cause harm and therefore prompts the need for ergonomic changes in the workplace. One limitation to using this method is that REBA scores are obtained through manual calculations, which can result in subjective observations and cause inaccuracies in the determination of angles. The development of automated REBA systems using computer vision and digital image processing can help automate and create an improved level of consistency and objectivity when assessing postures with REBA. The effectiveness of automated REBA systems such as those discussed above will heavily depend on how well you are able to capture images, have the appropriate lighting conditions, and get the workers and apparatus positioned accurately.

The scope of the present study is subject to three major limits. First, the automated REBA system relies upon images captured at the time of the recording, which does not allow for capturing real-time movement. Second, there have been no evaluations of the automated REBA system in a variety of occupational settings, thus limiting generalizability. Last, the automated REBA system does not incorporate information on dynamic forces and loads created by the use of a wearable device; thus, there is no ability to include those variables in the REBA calculation process. In addition, if the camera angle is not accurate or if the photograph does not have the appropriate lighting conditions, there will be inaccuracies in the detection of the worker's posture.

To better capture the angles of workers' postures, future research will concentrate on creating multi-camera systems that work together with worn sensors to increase the depth of the data collected from different locations. By creating a diverse dataset with multiple workplaces and industries, future projects will also provide greater reliability for this type of system. Machine learning could then be utilized to help automate the classification of risk levels and provide adaptive learning based on worker profiles. Research on the effectiveness of interventions based on the Modified-REBA method will provide better evidence for the practical application of improving workplace safety and health for workers who use the Modified-REBA system.

In general, the improvement of ergonomic assessment methodologies using Industry 4.0 technologies and by working towards meeting the Sustainable Development Goals (SDGs) will offer great benefits to developing countries by enhancing occupational health and creating sustainable MSMEs. The computer vision solution based on the Modified-REBA method not only supports improving ergonomic monitoring but also supports the advancement of the Sustainable Development Goals (SDGs) by increasing the viability of Micro, Small, and Medium-scale Enterprises (MSMEs) in developing countries.

## Acknowledgement

This work is supported by Universitas Kristen Maranatha, Indonesia.

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