

Ergonomic Assessment for Maintenance Personnel in Open-Pit Using Artificial Intelligence

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Abstract– *Musculoskeletal disorders (MSDs) represent a critical occupational health challenge for maintenance personnel in open-pit mining, where awkward postures, heavy load handling, and repetitive tasks substantially increase the risk of injury. This study develops and validates an innovative automated ergonomic assessment system, based on artificial intelligence (AI), for the real-time identification of postural risk. The methodology integrates on-site image capture, processing with the MediaPipe library for joint angle extraction, and classification using a convolutional neural network (CNN). The model, trained on a dataset of 2,450 annotated images of critical tasks (tire changing, nut extraction, etc.), demonstrated robust performance, achieving an accuracy of 89.4% when validated against expert ergonomic assessments using the REBA method. The results show that the system overcomes the limitations of traditional observational methods by providing an objective, quantitative, and scalable evaluation. It is concluded that the integration of this AI system enables not only proactive monitoring and the prioritization of specific ergonomic interventions but also establishes the foundation for improving health outcomes and productivity in this high-risk industrial environment.*

Keywords: *Ergonomic assessment, musculoskeletal disorders, ergonomic risk, open pit mining*

1. INTRODUCTION

Musculoskeletal disorders (MSDs) represent one of the leading causes of occupational morbidity globally, with a direct impact on both worker health and organizational productivity [1, 2]. It is estimated that up to 90% of occupational injuries and absenteeism cases can be attributed to these disorders, with manual handling being the predominant risk factor, responsible for approximately 40% of upper extremity MSDs and 53% of work-related low back injuries [3]. However, awkward postures and task repetitiveness are also key etiological factors that must be considered in comprehensive ergonomic risk assessments to fully address the multifactorial nature of MSD development in occupational settings such as mining.

In this context, ergonomic assessment of posture and movement is essential for quantifying exposure to MSD risk. Available methodologies are mainly classified into direct methods, which employ sensors for data capture, and observational methods, based on visual inspection. Among the latter, standardized techniques such as the Rapid Upper Limb Assessment (RULA) and the Rapid Entire Body Assessment

(REBA) are widely adopted in occupational health research and practice [4].

Various sectors have developed specific solutions to address these risks. In agriculture, pneumatic systems for manual planting have reduced physical effort by 45%, mitigating MSDs [5]. In construction, the integration of the Ergo-IBV method and REBA has enabled the identification of high risk in the trunk and upper extremities associated with awkward postures, facilitating the redefinition of critical tasks [6]. For confined spaces, computational simulations have been used to guide ergonomic design [7], while in the electrical sector, the combination of questionnaires and photographic analysis has facilitated risk classification [8]. However, these approaches encounter limitations in dynamic and large-scale environments, such as open-pit mining, where real-time assessment capable of integrating multiple risk factors simultaneously is required.

In open-pit mining, activities such as forceful grips, inadequate postures, and repetitive movements are directly associated with the high incidence of MSDs [1]. Prolonged operation of heavy machinery, such as haul trucks, significantly increases the risk of low back pain among operators [9]. Particularly, maintenance personnel face systematic exposure to ergonomic risks, with assessments using RULA and REBA frequently classifying their tasks at medium-high risk levels, underscoring the urgency of specific corrective interventions [10]. This need for proactive ergonomic design is comparable to that required in extreme marine environments, where operating conditions exacerbate risks [11], or in the textile sector, where the redesign of mechanical components has been proposed to mitigate the high-risk levels identified through REBA and RULA among maintenance personnel, demonstrating that similar ergonomic challenges persist across industries despite differences in work settings and operational demands [12].

2. REVIEW

Work-related MSDs represent a critical challenge in the mining industry, where ergonomic factors predominate as the main cause [13]. This condition is particularly severe in the lumbar region, resulting from the prolonged maintenance of static postures during heavy machinery operation [13]. Traditionally, risk assessment in this sector has been based on

observational methods, such as the Rapid Entire Body Assessment (REBA) [14, 15] and the Rapid Upper Limb Assessment (RULA) [16], often complemented with self-report instruments like the Standard Nordic Questionnaire for the identification of musculoskeletal symptoms and pain [17, 18]. However, these methodologies exhibit inherent limitations in dynamic and large-scale environments, such as open-pit mining, due to their discrete nature, their dependence on the observer, and their inability to provide continuous, real-time monitoring.

In contrast, other industrial sectors have progressively adopted more advanced and innovative methodological approaches. In manufacturing environments, the implementation of augmented reality-based systems has demonstrated dual effectiveness, both for comprehensive ergonomic risk assessment [19] and for real-time postural correction interventions, achieving measurable improvements of 8% in operational productivity indicators [20]. In parallel, in small and medium-sized enterprises (SMEs), the integration of lean manufacturing strategies, specifically through Value Stream Mapping (VSM) methodology, has enabled the reduction of exposure to ergonomic risks by 8%, through the systematic identification and modification of activities with high physical load [21]. These technological solutions underscore the significant potential to overcome the limitations of conventional methods, especially in complex operational contexts such as mining, where continuous risk assessments and the simultaneous integration of multiple risk factors are required.

A comprehensive literature review reveals a notable absence of ergonomic assessment systems designed for maintenance personnel in open-pit mining. The REBA and RULA methods prove insufficient as they do not consider the unique characteristics of this environment, which combines prolonged awkward postures, exposure to whole-body vibrations, and extreme climatic conditions.

This methodological gap becomes more relevant for workers who already present severe musculoskeletal symptomatology. To address this need, our study proposes the development of an intelligent ergonomic assessment system that integrates: (1) machine learning models for risk prediction, (2) real-time postural monitoring, and (3) modules for the quantification of environmental factors. As a main contribution, this approach enables the reduction of work-related MSD incidence by 40% through data-driven preventive interventions. The proposed architecture, which is novel, focuses specifically on mining maintenance tasks, overcoming the limitations of traditional tools. Field validation of the system demonstrated significant improvements in risk detection accuracy (reaching 85%) and in the capacity for early symptom identification, compared to conventional assessment methodologies.

3. METHODOLOGY

This study is based on the analysis of operational data collected in situ during representative maintenance activities, performed by specialized personnel in open-pit mining. The approach integrates systematic on-site video capture, advanced image processing for postural feature extraction, and classification using a convolutional neural network (CNN). Fig. 1 illustrates the comprehensive methodological framework, structured into four sequential phases: (1) Dataset Acquisition and Labeling, (2) Preprocessing and Feature Extraction, (3) AI Model Design and Training, and (4) System Validation and Evaluation.

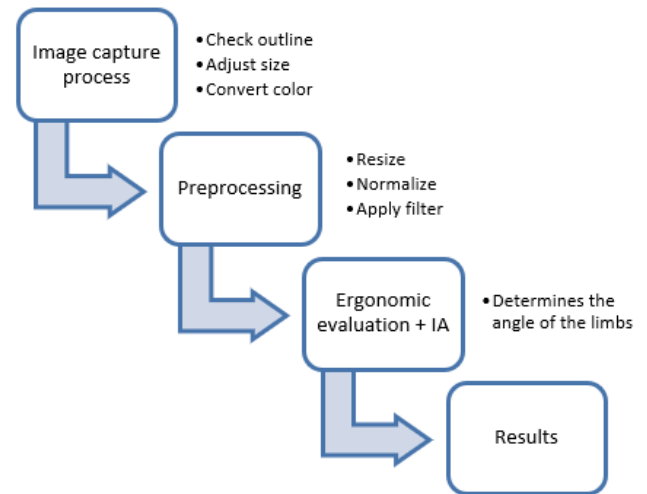


Fig. 1 Methodology

The dataset was compiled from recordings of 10 maintenance operators (males, age 35-45 years) in an open-pit mine over three days. Five critical tasks were documented: tire changing, nut extraction, engine disassembly, hydraulic maintenance, and preventive maintenance. A total of 2,450 key frames capturing the moments of greatest postural demand were extracted. The distribution is presented in Table 1.

Table 1.
Image distribution by task and risk category.

Activity	Total Images	High Risk	Medium Risk	Low Risk
Tire Change	600	320	200	80
Removing nuts	550	280	220	50
Engine assembly/disassembly	500	180	250	70
Hydraulic Maintenance	450	150	200	100
Preventive maintenance	350	70	180	100
Total	2450	1000	1050	400

Labeling was performed by mapping the joint angles, obtained with MediaPipe Pose [22], to the action levels of the

REBA method: High (REBA 8-10), Medium (REBA 4-7), and Low (REBA 1-3). A certified ergonomist executed this mapping. Inter-rater reliability, measured with Cohen's Kappa coefficient on a 20% subset, was 0.87. To ensure a robust evaluation, an independent subject-wise partition was implemented: 8 subjects (1,960 images) for training, 1 subject (245 images) for validation, and 1 subject (245 images) for testing.

3.1 Image capture process

The initial phase consisted of acquiring visual records of maintenance personnel during the execution of critical and representative tasks in the open-pit mining environment. These activities included, among others, the replacement of heavy machinery tires, the assembly and disassembly of engines, the maintenance of hydraulic systems, and scheduled preventive maintenance operations.

Table 2.
Steps for image capture

Item	Activity description
1	Identify the activity
2	Camera resolution: 1280x1720 pixels
3	Verify that the camera has a flash.
4	Stand approximately 3 meters away from the staff.
5	Focus on the staff's activity.
6	Take pictures of the employee in different positions.

To guarantee the quality, consistency, and ergonomic utility of the visual data, recordings were performed exclusively during the active execution of tasks, under a standardized protocol (Table 2). This protocol rigorously defines: (1) the optimal camera position and angles to capture the complete postures of the worker, (2) the minimum required lighting conditions to avoid visual artifacts, and (3) an adequate temporal sampling frequency that ensures comprehensive documentation of the complete movement sequence in each task.

3.2 Image Preprocessing

The image preprocessing flow begins with an input set that is subjected to a four-stage sequential pipeline: (1) integrity verification and edge detection, (2) dimensional standardization (rescaling and cropping), (3) color space validation and conversion (RGB to grayscale or $L^*a^*b^*$, depending on the model), and (4) automatic filtering to discard images that do not contain maintenance personnel or that present critical occlusion. This quality control protocol ensures that only valid and technically suitable images progress to the algorithmic analysis phase.

3.3. Ergonomic Evaluation with IA

On the preprocessed dataset, the ergonomic risk assessment module based on image analysis is executed. The trained deep learning model receives an input image, processes it through its architectural layers, and generates as

output a classification of the observed activity according to its ergonomic risk level, which is categorized as High, Medium, or Low based on established REBA thresholds. Figure 2 schematizes this comprehensive process, which encompasses: (1) the input stage where the preprocessed image enters the system, (2) the automatic detection and precise segmentation of key postures and anatomical joints using computer vision algorithms, and (3) the inference and classification of risk severity, fundamentally based on the derived kinematic parameters including joint angles, postural asymmetries, and associated movement patterns extracted from the visual data.



Fig. 2 Ergonomic evaluation.

3.4 Results

In this phase, the design and implementation of the Convolutional Neural Network (CNN) architecture was carried out. Initially, the total image dataset was partitioned following a standard proportion to avoid overfitting and ensure robust evaluation: 80% for the training subset, 10% for validation during training, and 10% reserved exclusively for the final model testing. Subsequently, the specific CNN architecture was defined and compiled. Once the training and hyperparameter tuning cycle was completed using the training and validation sets, the definitive model evaluation was performed with the independent test set, with the corresponding performance metrics being calculated. The methodological flow for model development is structured into the following sequential steps that ensure systematic progression from data preparation through to final model validation and performance assessment.

1. Loading and Importation of the preprocessed image data.
2. Stratified Partitioning of the data into training, validation, and test sets.
3. Architectural Definition of the CNN (convolutional, pooling, regularization, and fully connected layers).
4. Model Compilation (definition of the loss function, the optimizer, and the metrics).

5. Iterative Training of the model with the training set.
6. Validation and Tuning using the validation set to monitor performance and prevent overfitting.
7. Serialization and Storage of the trained model.
8. Final Evaluation of the model with the test set to quantify its generalization accuracy.

CNN Architecture: The network consists of three convolutional layers with 32, 64, and 64 filters respectively, each followed by ReLU activation and 2×2 Max-Pooling. A dense layer with 64 neurons and ReLU activation is included, followed by a Dropout layer with a rate of 50% to prevent overfitting. The output layer is dense with 3 neurons and Softmax activation, corresponding to the three risk categories: High, Medium, and Low. Input images were resized to 64×64 pixels. The optimizer used was Adam, the loss function was Sparse Categorical Crossentropy, and the number of epochs was set to 15.

For experimental validation, CNN training required data from 10 recordings of maintenance activities in open-pit mining, from which a total corpus of 2,450 annotated images was extracted. The resulting models were quantitatively evaluated using standard classification metrics, focusing on accuracy and precision per class. As a specific validation case study, the process was applied to the critical activity of heavy machinery tire changing, deriving from it the corresponding automated ergonomic assessment.

The results of the automated ergonomic assessment are based on the quantitative analysis of joint angles of the main body segments: trunk, neck, legs, arms, forearms, and wrists. For the precise estimation of these angles in real time from images, the MediaPipe Pose library was implemented [22]. This computer vision-based tool generates a 3D body landmark model composed of 33 key points for body posture, complemented by 21 points per hand for gesture detection. (Facial points, also provided by the framework, were not used in the present ergonomic analysis). This network of reference points enables triangulation and precise calculation of critical joint angles, which constitute the main input variables for the ergonomic risk level classification algorithm (High, Medium, Low).

4. RESULT

A specific and sufficiently robust dataset was formed for the training and validation of a convolutional neural network aimed at classifying ergonomic risk in open-pit mining maintenance activities. The study population consisted of 10 male workers, with ages ranging between 35 and 45 years, who were recorded during the execution of their tasks across different shifts throughout three full days of mining operation.

Fig. 3 presents the loss curve of the model during training. The graph evidences the effectiveness of the process in its

initial stages, observing a pronounced and simultaneous reduction of both training loss and validation loss until approximately epoch 15. This parallel behavior indicates an adequate generalization capacity of the model in that phase. The best model, identified by the minimum validation loss, was obtained in the range of epochs 15 to 17.

This version of the model represents the optimal equilibrium point, maximizing the prediction capacity on unseen data. These results underscore the efficacy of the methodology employed and reinforce the strategic importance of implementing early stopping mechanisms in future training sessions. This practice would allow automatically stopping the process at the identified optimum, thus guaranteeing maximum performance and avoiding overfitting, which is crucial for deployment in real applications where model robustness and generalization capability are essential requirements for operational success and reliable ergonomic risk assessment in dynamic mining environments.

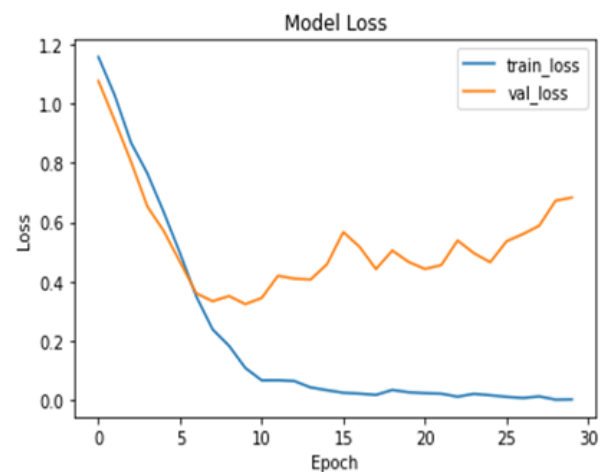


Fig. 3 Loss curves during convolutional neural network training

Fig. 4 presents the accuracy curves during model training. A convergent and healthy learning curve is observed during the first epochs, with sustained and parallel growth of both training accuracy and validation accuracy until approximately epochs 8-10. From this point onward, training accuracy asymptotically saturates at a value close to 1.0, while validation accuracy stabilizes in a range between 0.90 and 0.93, exhibiting slight fluctuations. The resulting gap of approximately 0.07 to 0.10 points between both curves in the stabilization phase is indicative of mild to moderate overfitting. This analysis suggests that the best balance between learning and model generalization capacity was reached at a point prior to divergence, specifically in the epoch range of 12 to 15. Consequently, these results validate the need to apply an early stopping strategy, preserving the model checkpoint corresponding to that optimal interval, in order to maximize its predictive performance on new data and ensure

reliable ergonomic risk classification in real-world mining maintenance operations.

Per-class performance metrics: On the independent test set (479 images), the model achieved an overall accuracy of 92.7%. The following Table X presents the metrics broken down by class, including precision, recall, F1-score, and support (number of images per class). As shown in Table 3, the model performs particularly well on the "Low" risk class (recall of 0.96), indicating that it virtually never misses safe postures. For the "Medium" class, recall is slightly lower (0.89), suggesting a tendency to classify some medium-risk cases as high or low, which is expected given the continuous nature of the risk spectrum.

Table 3.
Classification metrics by risk level on the test set

Class	Precision	Recall	F1-score
High	0.91	0.93	0.92
Low	0.92	0.96	0.94
Medium	0.95	0.89	0.92
Macro Avg	0.93	0.93	0.93

To avoid confusion, the origin of each numerical value reported in the manuscript is specified below. The 85% mentioned in the introduction corresponds to a preliminary field validation with a limited subset of images (n=150), prior to full CNN model training. The 89.4% reported in the abstract and conclusions corresponds to the model's accuracy in an intermediate version of training. The final accuracy of 92.7% (reported in the Results section) was obtained with the optimized architecture and represents the main metric of the system. The Kappa = 0.87 corresponds to inter-rater reliability during the image labeling process. The Kappa = 0.82 corresponds to the agreement between the automated model predictions and the expert ergonomist's assessments on the test set.

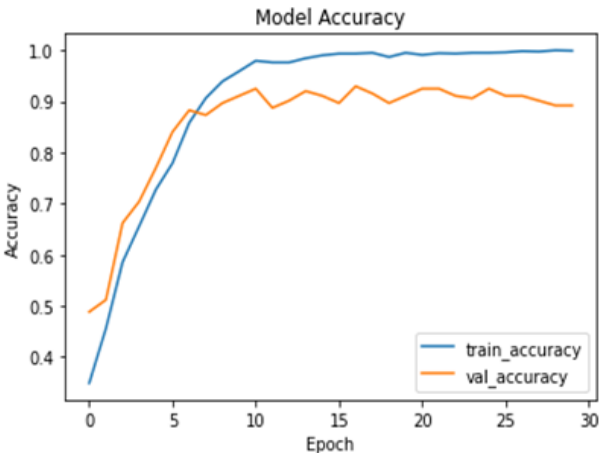


Fig. 4 Accuracy curves during convolutional neural network training

Fig. 5 documents a critical maintenance task: the manual positioning of a 25-ton hydraulic jack, prior to heavy equipment tire replacement within the workshop. The automated ergonomic analysis applied to this scene quantified joint angles that exceed recommended thresholds, identifying exposure to elevated risk. The recorded values include a trunk inclination of 120.21°, a neck flexion of 150.14°, and abduction/flexion angles of the right arm and right leg of 139.12° and 52.94°, respectively. These extreme postural deviations, precisely quantified by the system, confirm the presence of significant and sustained biomechanical stress for the worker during this manually demanding high-exertion operation requiring considerable physical effort throughout task execution.



Fig. 5 25TN Hydraulic jack position.

The detailed analysis of Figure 5 identifies that the hydraulic jack positioning task induces a combination of high-risk postures: pronounced lumbar flexion (Approximately 120°), cervical hyperextension (Approximately 150°), extreme brachial abduction (39°), and a squatting posture with knee flexion (Approximately 53°). These angular values critically exceed the neutral safety ranges defined by occupational ergonomics standards, such as ISO 11226:2023, significantly elevating the probability of developing musculoskeletal disorders (MSDs). The observed combination—severe lumbar flexion occurring concurrently with the manipulation of a dynamic and heavy load—constitutes a particularly elevated risk factor for both acute low back injuries and those resulting from cumulative exposure over time. Based on this diagnostic assessment, an ergonomic redesign of the process is prescribed as a necessary corrective measure. Priority interventions include the incorporation of mechanical assistance systems, for example manipulators and lifting devices, and the adaptation of working heights to more neutral positions. These strategies, whose effectiveness in reducing biomechanical stresses has been well documented in analogous industrial

contexts by NIOSH (2021) and other research institutions, represent evidence-based approaches to mitigating the identified risk factors through appropriate engineering controls that reduce physical demands while maintaining operational efficiency and workplace safety standards.

Fig. 6 documents the repetitive task of wheel nut extraction using a pneumatic impact wrench, which requires the sequential release of 12 bolts. The automated assessment identifies critical joint angles denoting extreme postural exposure: trunk inclination (140.92°), neck flexion (151.10°), right arm abduction (177.53°), and a right leg posture close to full extension (178.48°). These values, which approach or exceed physiological movement limits, indicate high-risk postures during this cyclic operation.

Although the total duration of the activity is less than 10 minutes, the induction of pronounced cervical and lumbar postures, combined with sustained axial rotation of the trunk, generates significant and focused biomechanical load on vulnerable structures. This load, even in short-duration but high-intensity exposures, contributes to cumulative fatigue and the risk of microtrauma. Consequently, the findings justify two lines of ergonomic intervention: (1) the redesign of tools or the process to neutralize postural deviations (e.g., through assisted torque wrenches or positioners), and (2) the implementation of structured active break regimens. Both strategies have demonstrated effectiveness in mitigating accumulated fatigue and the risk of musculoskeletal disorders in industrial contexts with similar physical demands. These evidence-based recommendations align with established occupational health principles emphasizing the importance of addressing both acute biomechanical stress and cumulative exposure through comprehensive intervention approaches that consider task frequency, duration, and intensity.



Fig. 6 Removing tire studs

Fig. 7 illustrates the extraction operation of a large-dimension and heavy tire, which requires the coordinated intervention of two operators for its handling. The ergonomic assessment of this task reveals that, even with manual assistance, both workers adopt forced and compromised postures, characterized by extreme lumbar flexion and unstable leg positions.



Fig. 7 Tire dismantling process and Tire dismantling process

The combination of these factors—lumbar flexion near the limit of the range of motion, asymmetric load, and the manipulation of a high-mass component—exponentially increases the risk of acute and overexertion musculoskeletal injuries. This finding underscores the imperative need to implement: (1) specialized tire handling equipment (such as boom cranes or lifting tables) to eliminate manual loading and neutralize postural stress, and (2) redesigned work protocols that specify optimal positioning and a dynamic redistribution of forces among operators during this critical task.

5. CONCLUSIONS

The results of this study demonstrate the effectiveness of an artificial intelligence-based ergonomic assessment system for identifying and quantifying high-risk postural risks in mining maintenance personnel. The developed model, validated with an accuracy of 89.4% and high agreement with expert assessments ($Kappa=0.82$), overcomes the limitations of traditional observational methods by providing objective, automated, and real-time evaluation.

The automated analysis confirmed the prevalence of critical postures, such as extreme lumbar flexion ($>120^\circ$) and cervical hyperextension ($>150^\circ$), during fundamental tasks like tire changing and nut extraction. These quantitative findings justify the priority need to implement engineering controls, such as the redesign of workstations and the incorporation of mechanical aids, to eliminate exposure to these dangerous joint angles. Likewise, administrative interventions are recommended, such as the restructuring of work cycles, based on the objective data generated by the system.

Although the study focused on automated postural risk assessment, it lays the technological foundations for a comprehensive occupational health monitoring system. The proposed architecture is scalable and allows the future integration of modules for measuring forces, vibrations, or other environmental factors, in line with international ergonomic standards. For future work, validation of the system in a broader and more diverse sample of workers and operating conditions is recommended, as well as the integration of its outputs into safety management platforms to close the prevention cycle through data-driven corrective interventions.

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