

Application of Convolutional Neural Networks (CNNs) for Work Ergonomics Analysis

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Abstract - Musculoskeletal disorders (MSDs) are a leading cause of work-related disability and absenteeism globally, often stemming from improper and repetitive workplace postures. Traditional ergonomic assessment methods, such as REBA and RULA, rely on manual evaluations that are inherently subjective and limited in scalability. This study presents a novel approach utilizing Convolutional Neural Networks (CNNs) to enhance the accuracy and efficiency of ergonomic risk assessments. A dataset of 1,330 workplace posture images, annotated using the REBA methodology, was analyzed through key point detection algorithms and processed with tools like Kinovea and Roboflow. The trained CNN model achieved remarkable performance metrics, including 99.9% precision, 100% recall, and 99.5% mean average precision (mAP). These results highlight the model's capability to classify workplace postures as correct or incorrect with high accuracy, surpassing the limitations of traditional methods. This automated approach not only eliminates subjectivity but also provides a scalable solution for MSD prevention, significantly improving workplace ergonomics. The findings of this study underscore the potential of integrating AI-driven tools with established ergonomic practices to optimize worker health and productivity in industrial environments.

Keywords: ergonomics, convolutional neural networks, REBA, posture analysis, key point detection, workplace risk prevention.

1. Introduction

Occupational musculoskeletal disorders (MSDs) are among the most reported injuries in the workplace, affecting muscles, nerves, tendons, and joints. These MSDs are linked to various occupational risk factors, such as excessive use of force, awkward postures at work, and prolonged permanence [1]. Around 1.7 billion people worldwide are affected by MSDs, making them the fourth factor with the greatest impact on the overall health of the population [2].

Ergonomic risk assessment has become a priority for organizations looking to improve the well-being of their employees while also reducing the costs associated with occupational health issues. The total costs of injury-related work disruption are estimated to be up to 2% of the European Union's gross domestic product, equivalent to €240 billion [3]. Despite traditional ergonomic assessment methods have proven useful in identifying high-risk postures, these methodologies often rely on subjective and manual assessments, which can lead to distortions and difficulties in their large-scale application. Accordingly, this study presents a novel approach utilizing Convolutional Neural Networks (CNNs) to improve the accuracy and efficiency of ergonomic risk assessments.

2. State of the Art

2.1. Ergonomics

Ergonomics is a discipline that studies the relationship between people and their work environment, including tools and the work environment in general, and is made up of various areas of knowledge, such as biological, medical, and technical sciences, among others [4]. In recent years, awareness of the relevance of ergonomics in the workplace has increased, as its purpose is to optimize the design of workspaces and reduce the risk of developing work-related musculoskeletal disorders [5]. This is particularly relevant in work sectors that involve repetitive or prolonged physical tasks. Figure 1 shows the incident rates of MSDs for different industries.

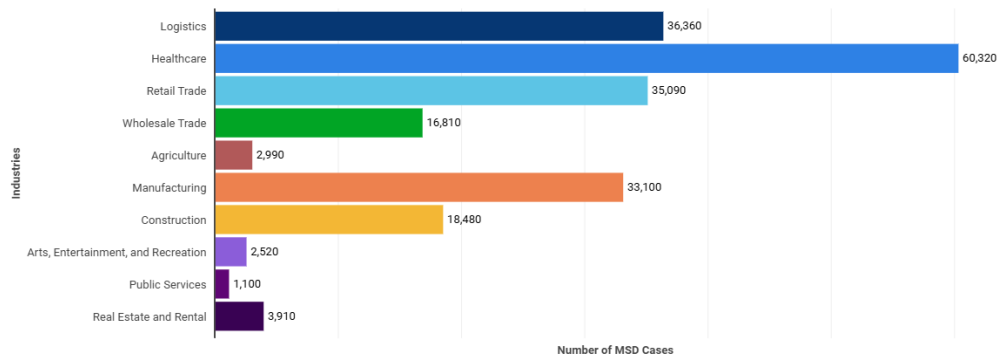


Fig. 1: The industries with the highest MSD rates. Information obtained from Ergonomics for the prevention of musculoskeletal disorders [6]. Own elaboration.

Work-related MSDs are injuries or pain to joints, muscles, nerves, or tendons, caused by repetitive tasks or awkward postures [7]. Thus, it is essential to identify and mitigate these risks in the workplace to prevent their appearance. Ergonomic risk assessment allows detecting and studying postures that may affect employee health [8]. This assessment identifies ergonomic hazards in the workplace, assesses the associated risk, and proposes interventions to reduce the likelihood of MSDs [9]. These assessments help prioritize the areas of greatest risk and adapt the work environment.

2.2. Traditional methodologies for ergonomic analysis

Ergonomic assessment in work environments is essential for optimizing both workstations and tasks performed. In certain legal contexts, companies are required to carry out these assessments. Currently, most ergonomic assessments are carried out using observational methods [10]. Each method produces a score that combines different risk factors, generating a value that helps determine whether the risk is within acceptable limits [11].

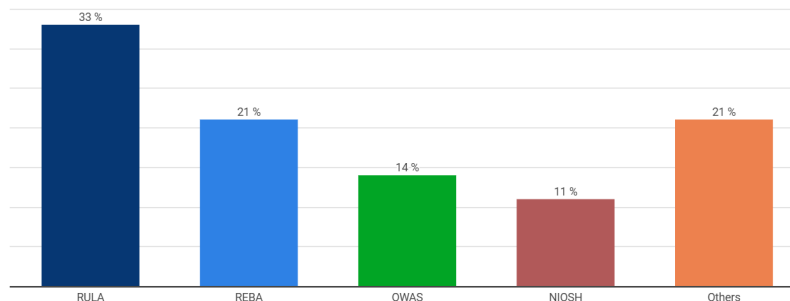


Fig. 2: Comparison of ergonomic methods used in the studies. Adapted from Ergonomics Evaluation Using Motion Capture Technology [12].

Among the traditional methodologies of ergonomic assessment, REBA, RULA₂ and OWAS stand out (Figure 2). Each of these methods focuses on different aspects of postural analysis. REBA assesses risks throughout the body, considering posture, strength, and frequency, being useful for detecting harmful movements [13]. The variety of work activities and the challenges present in today's industrial tasks make ergonomic assessment manual tools, such as checklists and spreadsheets, require significant effort and rely heavily on the specialist's expertise [5]. While observational methods are accessible, one in three professional assessments does not correctly estimate the level of risk of developing musculoskeletal disorders [14]. This shows the need for automated and digital tools that optimize the process, reducing subjectivity and improving accuracy in the identification of ergonomic risks.

2.3. Neural Networks

Neural networks (NNs) are computational models inspired by the structure and function of the human brain, consisting of interconnected layers of nodes (neurons) that process and learn patterns from data. NNs are efficient and easy-to-learn tools that support decision-making processes. Since most NNs are data-driven, their performance is directly related to the quantity and quality of data used for their training [15].

Recent studies have proposed the integration of traditional ergonomic methods with NNs to improve the accuracy in the measurement of postural risks; however, there is a gap in the comparison of different types of networks and functions, which makes it difficult to identify the most appropriate approach to optimize these methodologies [9].

Neural networks applied to ergonomics comprise two main types: convolutional neural networks (CNNs) and artificial neural networks (ANNs). CNNs are widely used for the analysis of postures and joint angles due to their ability to process images and spatial patterns, allowing postural risks to be assessed with high accuracy [7], they are also composed of multiple layers that, by performing a series of transformations, increase the predictive capacity of the model, making them particularly effective for analyzing large volumes of data in complex ergonomic assessments [17]. Inspired by the functioning of biological neural networks, ANNs excel in classification and regression tasks, and their backpropagation model facilitates the identification of patterns in ergonomic data, useful for detecting risk postures [16].

Table 1: Application of Neural Networks in Ergonomic Evaluation according to the literature.

Reference	Methodology	Neural network	Technology
[9]	REBA	Artificial Neural Networks	Analysis/Simulation Software
[14]	ROSE	Convolutional Neural Networks,	Video/Photo Cameras
[8]	REBA	Convolutional Neural Networks	Video/Photo Cameras
[5]	TACOS	Convolutional Neural Networks	Analysis/Simulation Software, Motion Capture Systems
[11]	REBA, RULA	Artificial Neural Networks	Analysis/Simulation Software
[7]	REBA	Convolutional Neural Networks	Analysis/Simulation Software
[18]	REBA, RULA	Convolutional Neural Networks	Motion Capture Systems, 3D Sensors/Scanners, Video/Photo Cameras
[19]	REBA, RULA, OWAS	Convolutional Neural Networks	Analysis/Simulation Software, Video/Photo Cameras
[20]	RULA	Artificial Neural Networks	3D Sensors/Scanners, Video/Photo Cameras
[1]	REBA	Convolutional Neural Networks	Video/Photo Cameras
[10]	OWAS	Convolutional Neural Networks	Video/Photo Cameras
[21]	OWAS	Convolutional Neural Networks	3D Sensors/Scanners
[22]	RULA	Convolutional Neural Networks	Video/Photo Cameras
[23]	RULA	Convolutional Neural Networks	3D Sensors/Scanners, Video/Photo Cameras

This review provides an overview of how neural networks are being integrated in the field of ergonomics for the identification and assessment of postural risks in different work domains. The studies analyzed also suggest that, as technologies continue to advance, neural network applications in ergonomics will continue to evolve, offering new opportunities for the prevention of musculoskeletal disorders and the optimization of working conditions.

3. Methodology

This study aims to design a neural network-based method for the assessment of ergonomic risks in work environments, using tools and methodologies to analyze workers' postures. The methodology, described in Figure 3, details the complete process that will be taken to carry out the study, from data collection to analysis and comparison of results.

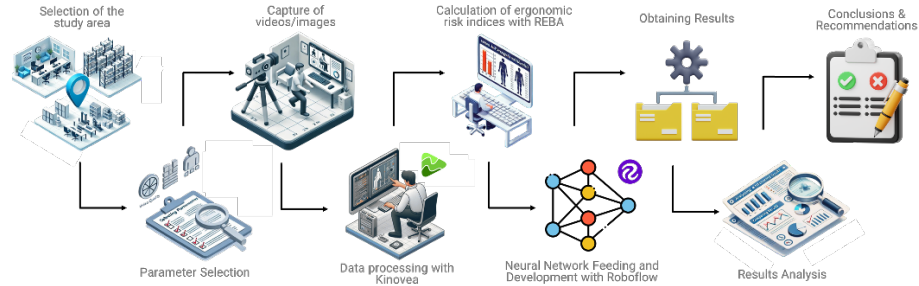


Fig. 3: Study methodology for the design of a neural network-based method for the assessment of ergonomic risks in work environments. Own elaboration.

3.1. Data processing with Kinovea

With the captured videos and images, Kinovea software was used for the initial processing of the data. Through this software, joint angles were measured and specific moments when the operator adopts critical or risky postures will be identified. These measurements provided quantitative information on the biomechanics of the operator in each task and allowed the calculation of the exact positions that present the greatest load or tension in the musculoskeletal system (Figure 4).

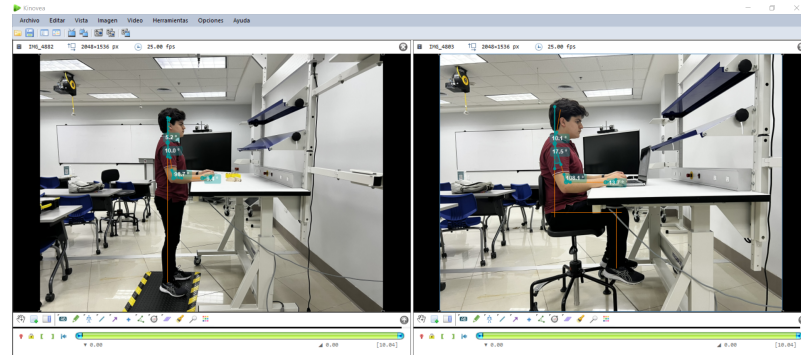


Fig. 4: Example of angle measurement using Kinovea software. Own elaboration

3.2. Calculation of ergonomic risk indices with REBA

The calculation of ergonomic risk indexes was carried out using the REBA (Rapid Entire Body Assessment) methodology, which evaluates work postures considering the position of joints, stability, and physical effort. Through tools such as Kinovea, critical angles were analysed and classified into risk levels using predefined tables and groups as stipulated in the REBA methodology [24]. These levels determine whether a posture requires immediate intervention or minor adjustments, which allows prioritising preventive actions to mitigate musculoskeletal disorders (Figure 5).

Score	1	2 or 3	4 to 7	8 to 10	11 to 15
Level	0	1	2	3	4
Risk	Negligible	Low	Medium	High	Very High

Fig. 5: Performance levels according to the final score obtained. Own elaboration.

Those with a risk level of 2, 3 or 4, which represent a significant ergonomic load for the operator and require intervention are considered incorrect postures. Those with a risk level of 0 or 1, which are considered within a safe range and do not require immediate modifications are considered correct postures.

3.3. Neural Network Feeding and Development with Roboflow

Data obtained from Kinovea was labeled according to correct and incorrect postures based on REBA criteria. This labeled data was then used in Roboflow to train a CNN. The network learned to automatically identify whether an observed posture is correct or incorrect based on the ergonomic patterns that were defined during parameter selection. The goal of the neural network is to evaluate each posture captured in the images and classify them into two categories: "correct" or "incorrect." The correct postures are those that minimize ergonomic risk, while the incorrect postures are those that represent a risk to the operator's health. The neural network was trained to identify both general postures (e.g., sitting or standing) and key points on the limbs that indicate a risk.

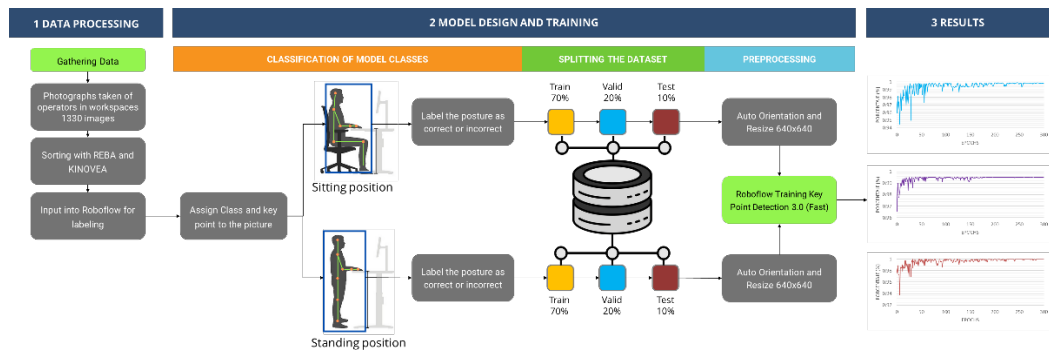


Fig.6: Architecture for the development of a convolutional neural network for ergonomic analysis. Own elaboration.

After training, the model will classify new images of the operator in the simulated environment. Performance metrics (accuracy, recall, and mAP) were used to assess the model's ability to accurately detect correct and incorrect postures. The analysis of these metrics served to validate the effectiveness of the model as an automated tool for the identification of ergonomic risks. The results were interpreted to identify the strengths of the model and possible areas for improvement.

3.4. Data Collection

The study was conducted using a total of 1,330 images captured with a mobile device within the industrial engineering laboratory simulating a real workspace, obtaining 524 standing postures and 806 sitting postures. These images were taken from strategic angles to analyze variations in the limbs of the body. It is very important in this case to make sure that the angles to be measured appear in true magnitude in the images, that is, that the plane in which the angle to be measured is located is parallel to the camera plane as shown in Figure 7.

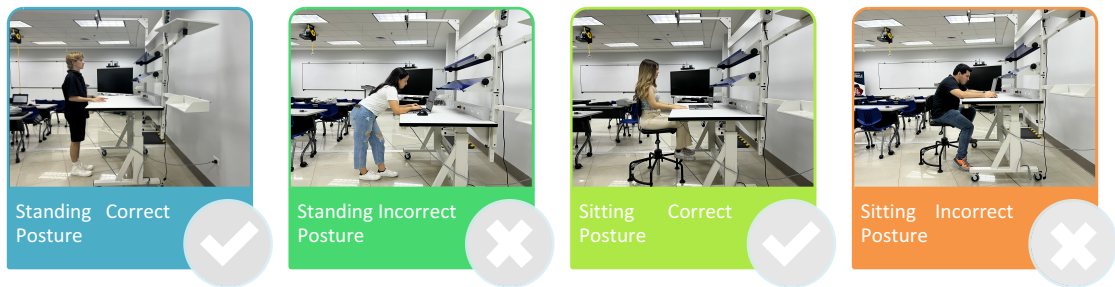


Fig. 7: Displays images suitable for ergonomic analysis. Own elaboration.

Results and Discussion

The image classification process was carried out in several stages, combining technological tools (KINOVEA) and ergonomic methodologies (REBA) to ensure accuracy and quality in the training of the model. The full results were organized into four tables according to the type of posture (sitting or standing) and level of risk (correct or incorrect).

Table 2: Sample of results obtained from the classification using REBA and Kinovea.

Operator Posture	Trunk	Neck	Legs	Arm	Forearm	Wrist	REBA Score	Risk Level
Correct Sitting Posture	0°	10.1°	90°	17.5°	108.1°	13.7°	2	1
Incorrect Sitting Posture	3.4°	44.4°	55.7°	27.3°	112.5°	31°	4	2
Correct Standing Posture	0	5.8°	0	9.6°	99.3°	9.7°	2	1
Incorrect Standing Posture	43.3°	53.4°	7.9°	59.4°	103.7°	14.4°	7	2

In total, 331 correct and 475 incorrect postures were classified in a sitting position, while in a standing position, 247 correct and 277 incorrect postures were recorded (Figure 8). This analysis using the REBA methodology and the Kinovea software allowed the classification of the postures to build a solid and representative database to train the ergonomic analysis model.

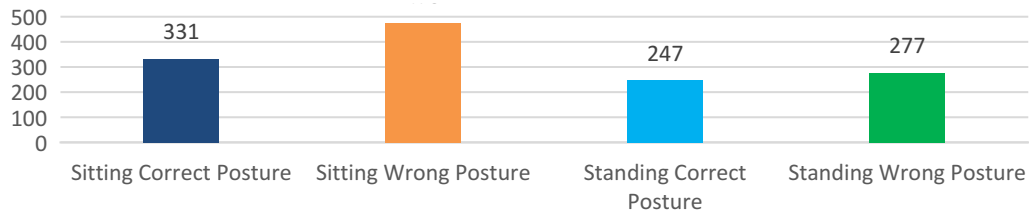


Fig. 8: Distribution of processed data using the REBA methodology and Kinovea software. Own elaboration.

The model training was based on the previously classified dataset. The images were tagged in Roboflow, obtaining a total of four classes: correct/incorrect sitting posture and correct/incorrect standing posture. The network was trained using the Roboflow 3.0 model with key point detection, allowing us to train the convolutional neural network and obtain the final model. The model was evaluated using the metrics mAP (Mean Average Accuracy), Accuracy and Recall, fundamental to measure its performance. These metrics provide detailed information about your ability to identify, classify, and retrieve relevant tags in images.

The model demonstrated exceptional performance metrics, achieving 99.9% accuracy, ensuring nearly all predictions were correct, and minimizing false positives. It attained 100% recall, effectively identifying all critical stances without omitting relevant tags, and a 99.5% mAP, reflecting a balanced and outstanding overall performance by integrating accuracy and comprehensiveness (Figure 9). The model demonstrated high performance in identifying correct and incorrect postures, achieving confidence levels ranging from 89% to 94% with an average of 92%-93% across all categories. It effectively identified correct sitting and standing postures, as illustrated in Figure 10. The consistent performance across all classifications, reflected by the narrow variability in confidence ranges, underscores the model's reliability in analyzing and classifying different types of postures. The main limitations of the model include its dependence on a dataset limited to controlled environments, which restricts its generalization to work scenarios with variations in lighting, clothing, or tools. In addition, it was designed for static postures, making it difficult to apply in dynamic movements. Finally, the accuracy of the analysis depends on reliable segmentation of key points, as errors at this stage affect ergonomic evaluation.

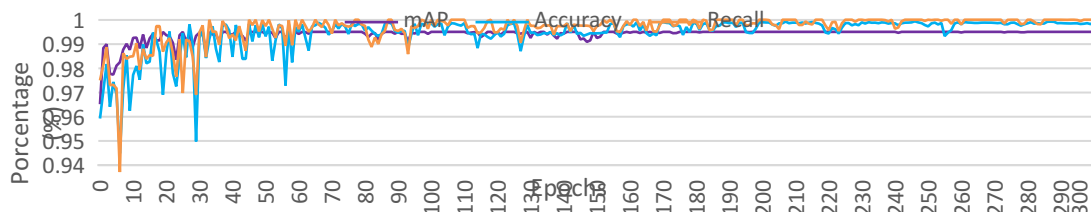


Fig. 9: Key performance metrics of the model obtained during training. Own elaboration.

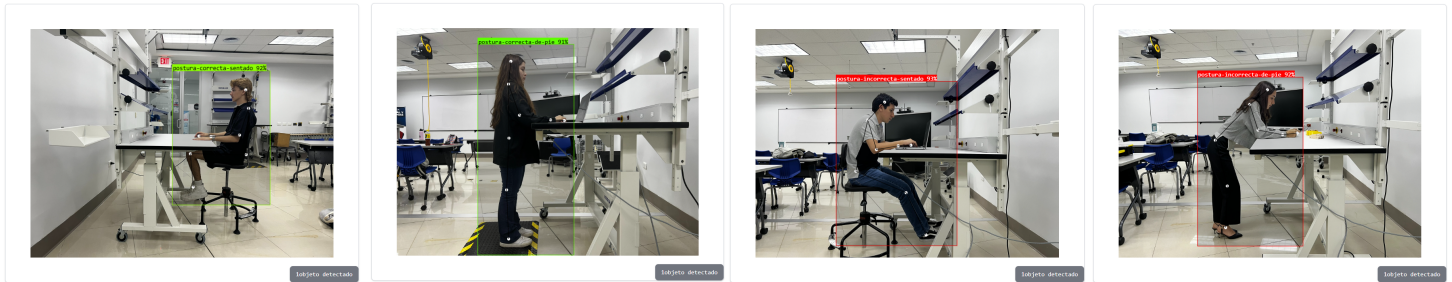


Fig. 10: Tests performed for correct and incorrect postures. Retrieved from Roboflow.

5. Conclusion

The analysis of work postures using the REBA methodology and the Kinovea software allowed the evaluation of 1,330 images in simulated conditions, identifying that 43.5% corresponded to correct postures and 56.5% to incorrect postures, evidencing significant ergonomic risks. Training a CNN in Roboflow proved to be an efficient tool for automating ergonomic analysis. With an average accuracy (mAP) of 99.5%, an accuracy of 99.9%, and a recall of 100%, the model identified correct and incorrect postures with high accuracy, reducing the subjectivity of traditional methods. In addition, it detected critical ergonomic patterns, optimizing postural risk analysis and providing practical solutions for the prevention of MSDs.

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