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A Real-Time Ergonomic Posture Analysis System for Surgeons in Operating Rooms Using YOLOv11

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ABSTRACT

Background: Surgical procedures involve prolonged static postures. There is, therefore, a great risk of musculoskeletal disorders since the high-risk factors are two: the procedure and the static posture. It is important to note that ergonomic posture analysis remains one of the measures toward the risk of MSDs. Unfortunately, existing methods of ergonomic assessment do not provide the surgeons with feedback in real-time.

Purpose: This study presents an Ergonomic Monitoring System based on artificial intelligence, which joins YOLO version 11 for real-time posture analysis and feedback with special reference to occlusion-heavy operating room scenarios. The system is designed to improve posture correction by means of automated, data-empowered ergonomic risk assessments.

Methods: The system detects key postural landmarks—neck, shoulders, back, and elbows—to calculate joint angles and classify postures using the RULA and REBA ergonomic models. A dataset of 700 annotated images was obtained in collaboration with the King Abdulaziz University Hospital and publicly available sources. Ground truth values were established using ergonomic risk models and expert validation. The system was evaluated against OpenPose and MediaPipe, with performance measured through standard pose estimation metrics.

Results: YOLOv11 outperformed both OpenPose and MediaPipe with respect to mean Average Precision (mAP), achieving 94.5% with a Precision of 95% and recall

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of 84.7%. Being able to give feedback in real-time through video and text will allow the surgeon to dynamically adjust his posture and reduce ergonomic risks effectively.

Conclusions : This study presents a real-time AI-based assessment tool for surgical ergonomics, which was not possible with manual evaluations. The real-time posture correction by the system would be a major step toward MSD minimization for surgeons. In the time to come, 3D pose estimation will be integrated, the dataset will be expanded, and fatigue tracking will be included to have a complete ergonomic assessment.

Keywords: Ergonomics, Pose Estimation, YOLOv11, Virtual Reality, Surgical Training

1 INTRODUCTION

1.1 Importance of Ergonomics Assessment for surgeons

Human factors engineering—an ergonomics concept involves the design of work environments to fit human limitations and capabilities. Designing the workplace right under ergonomics ensures safety as well as efficiency and productivity, particularly in physically demanding work, such as surgery[1]. This is of special importance in surgical contexts, the OR environment has a significant impact on the well-being of the surgeon and the outcome of the patient. Worldwide, over 70% of surgeons experience pain in the musculoskeletal system due to longstanding static positions, difficult movements, and repeated tasks during complex surgeries[2].

These ergonomic issues increase the risk of MSDs, which contribute to healthcare inefficiencies, early retirement, and poor-quality care.

While traditional assessments of ergonomics, such as self-reports and observational methods, are beneficial in their capacity to recognize dynamic, high-stressed OR situations, they lack the ability to do so. Future advances in artificial intelligence (AI) have the potential to revolutionize the industry. Specifically, pose estimation models have demonstrated a great degree of success in real time, non-invasive monitoring of posture in sports and rehabilitation. However, the use of these apps in the surgical profession is still in its infancy. The main research questions of this study are How can deep learning based pose estimation models YOLOv11 be used to give real-time ergonomic feedback for surgeons in occlusion-rich operating room environments

1.2. Study Objective

This research develops an AI-driven system for ergonomic evaluation that is based on the YOLOv11 design:

1. Real-time detection of key postures, the focus of attention is on the neck, shoulders, elbows, and back.
2. calculates the joint angles to classify postures as being safe or dangerous based on the RULA and REBA frameworks.
3. Provides immediate feedback that enables surgeons to alter their posture during surgery instead of analyzing the procedure afterward.

1.3. Study Contribution

This study bridges the gap in ergonomic assessment, especially for the surgical environment by using a real-time posture detection and feedback system with YOLOv11 model, respecting the state of the art. The major contributions and novelties of this research work are:

1. Real-Time Ergonomic Feedback System: YOLOv11 integration enables real-time actionable feedback on posture for surgeons while performing surgery. It calculates joint angles and classifies postures as "Good," "Moderate," and "High-Risk" levels of factors to address the limitations of traditional ergonomic assessment and the lack of real-time monitoring and adaptability[3].
2. Advanced Occlusion Handling: Due to the self-attention mechanism of the model, even occlusion-heavy environments can be well accommodated for joint detection in bodies. An operating room is a good example where surgical instruments and personnel often obstruct key body parts.

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3. Edge-Device Compatibility: The lightweight design of YOLOv11 ensures scalability on edge devices and deployment for a practical solution in resource-constrained environments like ORs, thereby widening the accessibility of real-time ergonomic monitoring across diverse healthcare settings.
4. Innovative Data Augmentation: An alternative of data-augmentation techniques in the form of rotation, scaling, brightness adjustments, and simulated occlusions can make the system robust and generalizable for it to be able to work in real life with varying environmental conditions and postural complexities. This will guarantee robustness and generalization that is useful when adapting the system to various environmental conditions and postural complexities[4,5].
5. Interdisciplinary Applicability: Although the system was developed to support surgery, the general flexible framework and sturdy design permits its application to other fields, such as sports, rehabilitation, and industrial ergonomics, offering a real-time feedback mechanism to improve safety and performance.
6. Comprehensive Validation: It was tested with a high level of accuracy and relevance on a curated dataset of 700 annotated images sourced from publicly available surgical videos (650 images) and real OR images (50 images) provided by the Neurosurgery Department at King Abdulaziz University Hospital. Each image is labeled using Rapid Upper Limb Assessment (RULA)[6] and Rapid Entire Body Assessment (REBA)[6] frameworks, defining ergonomic risk based on joint angle deviations. The practical relevance and work applicability of the tool in real contexts for establishing an updated standard for ergonomic assessments in high-stakes environments is its biggest strength.

In this paper, we will address a critical gap in traditional ergonomic assessment methods in section 2, the methodology used to apply the system in section 3, and the result of system in section 4. Finally, the conclusion and future work in section 5.

2 RELATED WORK

Ergonomic assessment systems have advanced greatly from manual traditional methods to the very sophisticated AI-based solutions that are able to overcome all the challenges of self-occlusion, dynamic environments, and real-time posture monitoring. This is most important in high-stakes environments such as OR in which ergonomic risks to surgeons are enhanced because of sustained static postures, repetitive motions, and awkward body postures. Traditionally, ergonomic evaluations were based on self-reported data, observational analysis, and direct measurement instruments to identify risks associated with posture. Self-reported instruments, such as the Nordic Musculoskeletal Questionnaire (NMQ) and the Cornell Musculoskeletal Discomfort Questionnaire (CMDQ) were popularly utilized to collect data on physical discomfort and posture-related strain[7,8]. While these instruments have a value in understanding the experiences of workers, they are inherently subject to biases and tend to misinterpretation and inconsistency in the reporting of events[9].

Direct measurement tools, including accelerometers, inclinometers, and EMG sensors, provide data that is objective regarding the angles of joint, muscular activity, and the loads placed on the body[10,11]. While effective in controlled environments, their high costs, invasiveness, and lack of practicality for long periods of use, particularly in sterile surgical settings, present significant limitations[12].

observational methods, such as the Rapid Upper Limb Assessment (RULA)[13], the Rapid Entire Body assessment (REBA)[6],
and the Ovako Working Posture Analysis System (OWAS),[14] have been shown to be effective in the assessment of ergonomic risk. However, these approaches are slow, labor-intensive, and susceptible to variability between observers. They also lack the ability to provide constant or real time monitoring, which is essential in dynamic environments like the OR.

All traditional approaches have a shortfall in addressing the demands of high-stakes environments, they highlight the need for automated, non-interactive solutions that can provide instantaneous feedback with high accuracy and reliability.

Self-occlusion, or the condition where certain parts of the body are invisible due to the overlap of anatomical structures or surrounding objects, is still considered an open issue regarding ergonomic risk assessment. Especially when applied to a dynamic environment such as the operating room. Self-

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occluded pose estimation has been receiving very active attention recently in deep learning studies; this emphasizes the necessity to provide very effective feature extraction techniques for accurate recognition of posture. In their work,[15] designed a deep learning model capable of detecting major body joints either partially or fully occluded. This model CNNs with attention mechanisms that proved to be quite strong in estimating joint angles in highly occluded situations.

This relates closely to our work, which seeks to overcome challenges of occlusion in an OR scenario, wherein surgical instruments and personnel frequently occlude the critical postural landmarks. To further generalize the problem, recent works have also proposed temporal consistency mechanisms as well as enhanced CNN structures for robust occlusion handling in real-time scenarios. Skeletal refinement techniques based on Kinect have been proposed to effectively manage occlusion. This robustly accommodates accurate joint finding even in visually challenging scenarios[5]. In the light of this work, in our design,
we incorporate a self-attention mechanism within the YOLOv11 architecture to enhance the functionality of keypoint detection with very high reliability in real-time ergonomic monitoring.

Temporal consistency mechanisms further augment the pose estimation models by utilizing historical information to ensure the robust tracking of postures across frames[16] . These solutions not only enhance the ergonomic evaluations in ORs, although expand their scope to include sports and industrial environments, where the accurate recognition of posture is crucial to safety and optimization of performance.

Integration of AI into surgical workflows has brought ergonomic monitoring in operating rooms to significantly higher levels. AI-based systems allow automatic identification of surgical steps, with ergonomic best practices in them and hence reduce the manual burden on surgeons. It provides correction feedback of posture in real time, thus assisting the surgeon in being ergonomically right while operating. These include AI-driven systems for the automatic recognition of laparoscopic
workflow in operative steps and ergonomically setting the working conditions· These are new developments in the domain, wherein it can be seen that AI technologies can assist in creating safer working conditions, which will reduce the risk of work-related musculoskeletal disorders (MSDs) among surgeons.

Skeleton and shape models are crucial to the analysis of ergonomics, particularly in the estimation and reconstruction of human positions in three-dimensional space.

Parametric models like SMPL (Skinned Multi-Person Linear Model) offer robust solutions for tracking joint movements and posture alignment, enabling detailed ergonomic evaluations[3]. Temporal modeling, which ensures consistency across successive frames, increases the value of these models, making them appropriate for use in real time in healthcare and sports[4] . By combining skeletal models with automated tools that are driven by AI, real-time posture monitoring systems can provide immediate assistance, this diminishes the risk of MSDs and improves the well-being of practitioners.

The models, OpenPose, MediaPipe, and MoveNet, have become popular in ergonomics research because they can extract joint coordinates from video data and automatically assess posture.

Kim et al.[17] developed the OpenPose-based system for ergonomic posture analysis; it was based on determining RULA and REBA scores for ergonomic risk classification. OpenPose was validated against both motion capture systems and Kinectbased models. Accuracy in detecting postural deviations turned out relatively high, even in occlusion-rich environments. Their results proved OpenPose can be used as a reliable tool for semi-automatic ergonomic assessments in occupational applications. Likewise, Bagga & Yang[18] proposed an online risk assessment framework for evaluating posture deviations in manual lifting tasks. The framework integrated MediaPipe with a Long Short-Term Memory model. As a result, their system could give feedback in real-time. Thus, their work opened new optimization avenues for pose estimation models in reducing musculoskeletal risks via continuous ergonomic monitoring.

Among frameworks for estimating poses, YOLO (You Only Look Once) has become the most popular solution to real time object detection and posture surveying. Early iterations like YOLOv3 and YOLOv5 had impressive efficiency, but they were limited by the presence of occluding environments[19,20]. The recent YOLOv11 adds mechanisms for self-observation to improve the way they handle occlusion, heads that are free of anchors to improve their adaptability, and multiple scales of detection to increase their precision.

Based on these advances, this study employs YOLOv11 to address the limitations of previous models. This provides a new system of ergonomic assessment that is capable of real time posture detection and feedback in the OR.

3 METHODOLOGY

3.1 Data Collection and Annotation Phase

This study employed video recordings of surgical procedures conducted in OR environment to construct a comprehensive dataset representative of real-world surgical conditions. A data set of 700 frames was extracted from surgical videos available to the public (650 frames) varied sources guaranteeing variation and real images from the OR (50 frames) at King Abdulaziz University Hospital – postures captured authentically in live surgical settings. From these recordings, 700 frames were extracted, each capturing diverse postures commonly adopted by surgeons during procedures. The dataset was curated to reflect the complexities of OR scenarios, incorporating various angles, lighting conditions, and occlusions caused by surgical tools and personnel. dataset is available upon request from the author.

The annotation process utilized the Computer Vision Annotation Tool (CVAT), chosen for its precision and efficiency in high-resolution image labeling. Guidelines for annotation were derived from established ergonomic risk assessment frameworks, emphasizing joint angles and spatial relationships indicative of ergonomic safety or risk. Each image was manually annotated using RULA[13] and REBA[6] ergonomic risk frameworks, defining ergonomic risk levels based on:

- Neck Angles: Neutral (<10°), Moderate (10°–20°), High Risk (>20°)
- Shoulder Elevation: Neutral (<20°), Moderate (20°–45°), High Risk (>45°)
- Elbow Flexion: Neutral (90°–110°), Moderate (110°–135°), High Risk (<90° or >135°)
- Back Posture: Neutral (<5° deviation), Moderate (5°–20°), High Risk (>20°)

3.2 Data Augmentation

To enhance the robustness and generalizability of the model, a series of data augmentation techniques were applied:

- Rotation and Scaling: Random transformations simulated variations in viewpoints and body orientations, improving the model's adaptability to diverse postures.
- Brightness and Contrast Adjustments: Variations in OR lighting conditions were replicated through adjustments in brightness and contrast, preparing the model for fluctuating illumination.
- Occlusion Simulation: Artificial occlusions, such as surgical tools or partial obstructions by personnel, were introduced to train YOLOv11 to handle scenarios where body joints are partially obscured.

3.3 YOLOv11 Architecture

The key components in YOLOv11 are shown in figure 1

3.4 EfficientNet-B5 Backbone

YOLOv11 leverages the EfficientNet-B5 model for feature extraction, employing compound scaling to optimize network depth, width, and resolution. This ensures high-resolution spatial feature extraction while maintaining computational efficiency, enabling real-time operation critical for OR applications.

1. Path Aggregation Network (PAN) for Multi-Scale Feature Fusion:
   The inclusion of a PAN enables effective fusion of multi-scale features, enhancing the detection of both large and small anatomical landmarks. This capability is particularly important for ergonomic posture recognition, where subtle changes in joint alignment can indicate significant risks.
2. Self-Attention Mechanism for Occlusion Handling:
   YOLOv11 integrates a self-attention mechanism to dynamically focus on regions within frames that are partially occluded or ambiguous. This innovation enhances the model's ability to detect occluded joints, such as those obscured by surgical instruments or other personnel, ensuring accurate pose estimation under challenging conditions.

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3. Anchor-Free Detection Head:
   YOLOv11 employs an anchor-free detection head. This simplifies the detection process, reducing computational overhead and enabling greater adaptability to diverse poses and scales.

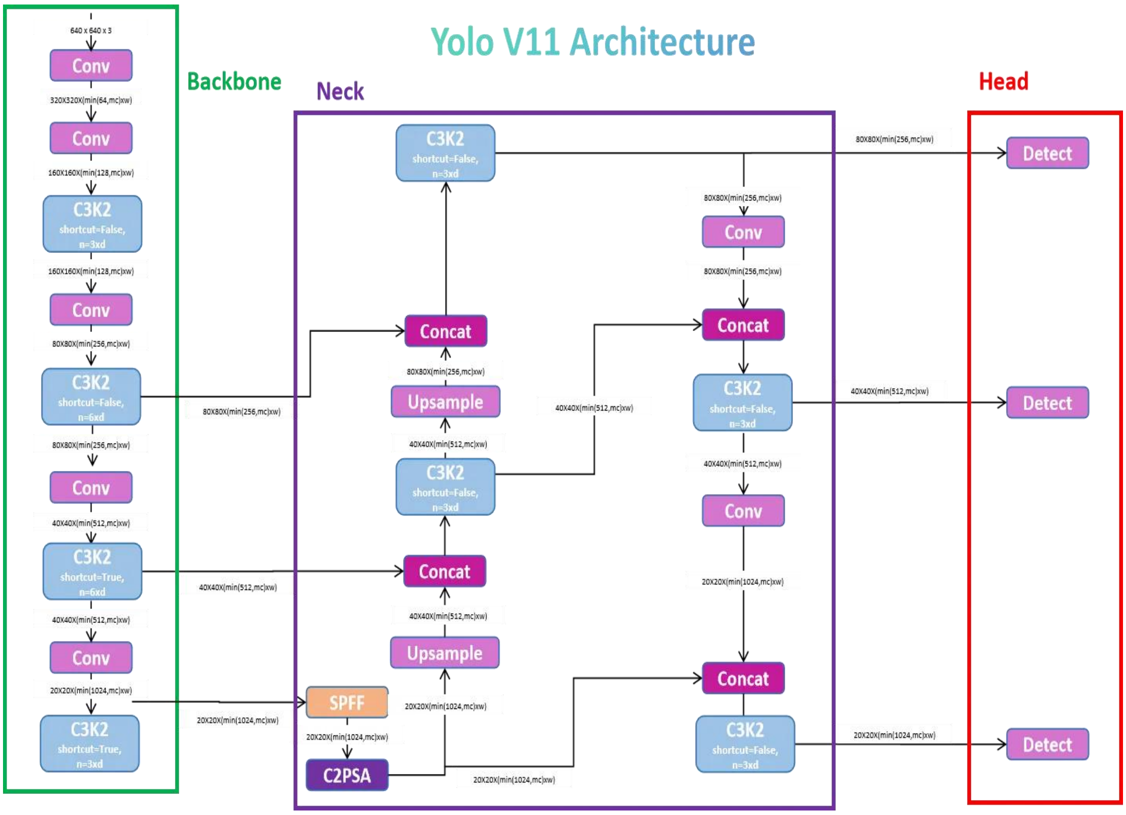

Figure 1. YOLOv11 architecture[21]

4. Real-Time Ergonomic Feedback Integration:
   YOLOv11 includes a feedback loop that continuously monitors joint positions and angles, providing immediate alerts when postures deviate from ergonomic safety thresholds. This real-time capability fosters awareness and allows for prompt corrective actions, reducing musculoskeletal risks for surgeons.
   The following points are Pose Estimation and Ergonomic Analysis Process in YOLOv11:

- Joint Detection and Localization: The model identifies key joints (neck, shoulders, elbows, and lower back) using the EfficientNet-B5 backbone and PAN to extract spatial features across scales.
- Angle Calculation: Detected joint coordinates are used to compute critical angles, such as neck-to-shoulder and shoulderto-elbow angles, which are pivotal for ergonomic assessments.
- Risk Classification: Based on ergonomic guidelines, the model classifies postures into “Good,” “Moderate,” or “HighRisk” categories by comparing joint angles to predefined thresholds. These classifications are displayed via a color-coded user interface to facilitate intuitive feedback. These classifications are displayed via a color-coded user interface to facilitate intuitive feedback. This classification was adopted from the measured body angles according to the modified rapid upper limb assessment, that is, angle deviated from the neutral position of various body parts[22] .

YOLOv11’s optimized architecture ensures low-latency, high-accuracy posture detection and risk classification, even under the spatial and temporal constraints of OR workflows. Its robustness to occlusions and capability to provide real-time feedback make it an invaluable tool for improving ergonomic safety in surgical settings.

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3.5 Training Setup

3.5.1 Dataset

We use a dataset comprising 700 annotated images of surgeons captured in OR settings. The images cover diverse poses under conditions that mimic real-world OR environments, such as occlusion and variation in lighting. Of the dataset, 90% for training and the rest 10% for testing to have postures well represented and balance for proper model evaluation. The 90-10 dataset split provides a good balance between keeping sufficient data for robust training that will allow generalization and not having too much data to cause overfitting. It balances model learning with a representative test set, which guarantees trustworthy evaluation in high precision tasks, such as ergonomic posture analysis.

3.5.2 Model

The system uses the YOLOv11n-pose model, an advanced framework for pose estimation in complex and dynamic environments. The state-of-the-art model version demonstrates multi-scale detection and self-attention capabilities, ensuring robustness towards occlusions and accuracy in detecting keypoints.

3.5.3 Environment

It was trained in a proper computational environment, defined as Hardware is Colab TPU v2-8, which has the ability for high-performance tensor processing with data and model scaling. Framework is PyTorch is a deep learning framework that is quite popular for being flexible and efficient when it comes to the implementation of pose detection models.

3.5.4 Training Parameters

The following were the training hyperparameters, balancing computational efficiency with model performance: -
Batch Size:4
Learning Rate:0.001
Optimizer: Adam, adopted because of its adaptive learning rate capabilities that enhance convergence during training. Epochs:100, to allow enough iterations for the model to effectively learn key features from the training data.

4 RESULTS AND DISCUSSION

4.1 Training and Validation Loss Analysis

The model's pose and box losses for both training and validation phases steadily decreased across 100 epochs:

- Pose Loss: Training loss reduced from 7 to 2, while validation loss stabilized around 2.5, indicating that YOLOv11 achieved consistent and effective learning.
- Box Loss: Training box loss decreased from 1.6 to 0.6, and validation loss stabilized around 0.9, demonstrating YOLOv11's capability in accurately localizing body joints, even under partial occlusion.

This figure 2 illustrates the complete set of metrics used to train and validate the YOLOv11n-pose model over the course of 100 epochs. The fields are organized into two stripes.

The YOLOv11n-pose model learns well and generalizes during training for 100 epochs. A few very important observed train and validation losses regarding box loss, pose loss, and objectless loss indicate how well the model learns in practice to detect and localize anatomical keypoints. At all levels, average precision continues raising with a direct parameter at varying levels of IoU thresholds from 50 to 95%; hence, in real terms, the balance between precision and recall of detecting and localizing body parts is obtained for both training and unseen validation datasets. These results show the model can be applied in an occluded environment, making it quite robust for real-time ergonomic monitoring and feedback in dynamic operating room settings.

4.1.1 Pose Precision curve

In figure 3 curve plots precision on the y-axis against confidence thresholds on the x-axis. It helps visualize how precision varies as you change the confidence threshold for predictions. It observed that all classes have a precision of 1.00 at a threshold of 0.898, it means that the model has a perfect precision score when it makes predictions with confidence scores equal to or above 0.898.

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4.1.2 Pose-Recall Curve

In figure 4, a recall of 0.898 suggests that the model is good at capturing true positives. It means that out of all actual positive instances, the model successfully identified about 89.8% of them. The confidence score of 0.00 implies that the model is making predictions regardless of how confident it is. This can mean that all instances are classified as positive, leading to a high recall

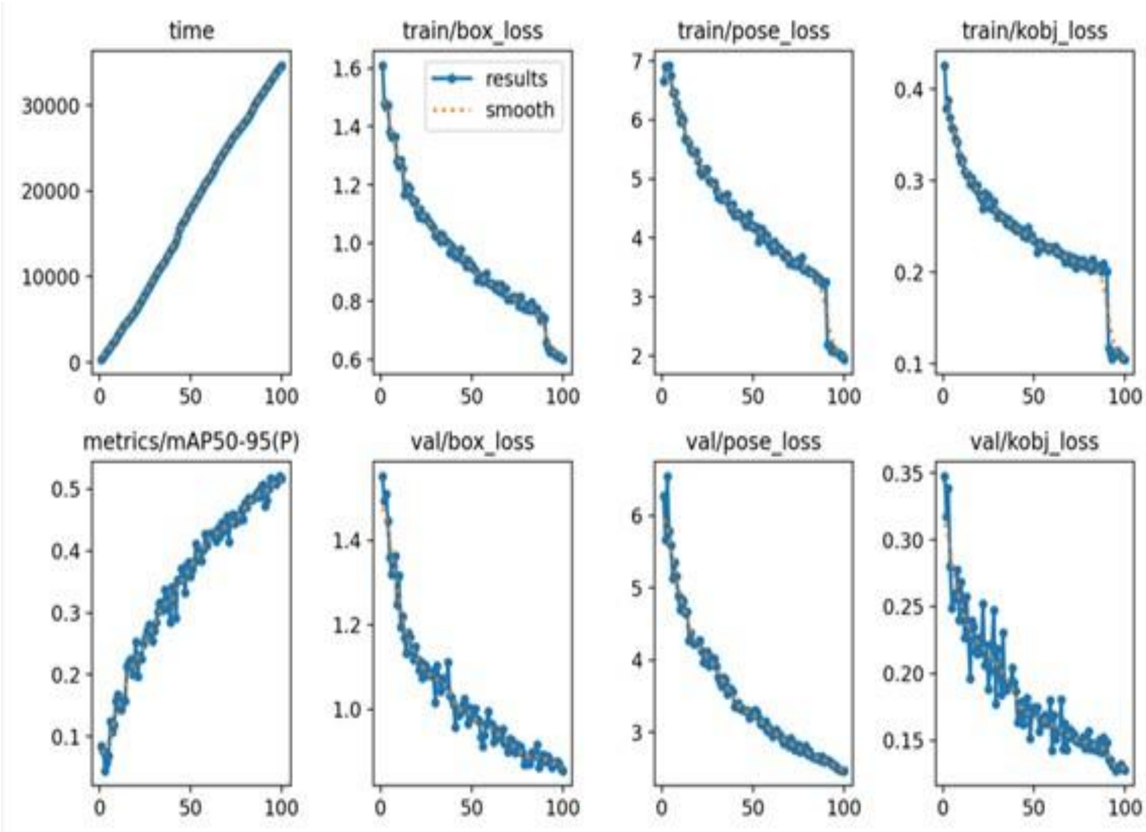

Figure 2. Training and validation performance metrics for the YOLOv11n-pose model across 100 epochs. The top row depicts training loss (classification and distribution focal loss) and precision/mAP metrics, while the bottom row visualizes validation loss, recall, and mAP metrics for bounding box and pose estimation. The results demonstrate steady improvements in accuracy and generalization throughout the training process.

4.1.3 Pose F-1 Curve

In figure 5, the F1-score is the harmonic mean of precision and recall, providing a balance between the two metrics, especially useful when dealing with imbalanced datasets. An F1-score of 0.9 at a confidence threshold of 0.752 suggests that your model is performing quite well at that point, effectively balancing precision and recall.

An F1-score of 0.9 indicates excellent performance, as it approaches the maximum value of 1. This means that the model is able to maintain both high precision and recall at the given threshold.

A high F1-score indicates that the model has a good capability of distinguishing between the positive and negative classes effectively.

4.1.4 Pose Confusion Matrix

Pose confusion matrices as shown in figure 6 may be perceived as rather technical apparatus developed for the purposes of assessing any given model's performance in detecting poses. This is essentially a breakdown of how well— at the granular level— the model predicts in comparison to ground truth. It could assist in pinpointing regions in which the model performs well or misclassify (providing actionable insights into what can be done to improve the model). The pose detection matrix is as follows:

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1. Ground Truth Key points (Columns): Actual anatomical keypoints as labeled in the dataset.
2. Predicted Keypoints (Rows): Keypoints detected by the model.
3. Diagonal values: The keypoint class for which the predictions were correct (true positives).
4. Off-Diagonal Values: Misclassifications; where in this case one keypoint was predicted when another was.

By studying this matrix, developers can concentrate on those classes having high misclassification rates to further improve the model's performance for tough cases, given occlusion or complex poses.

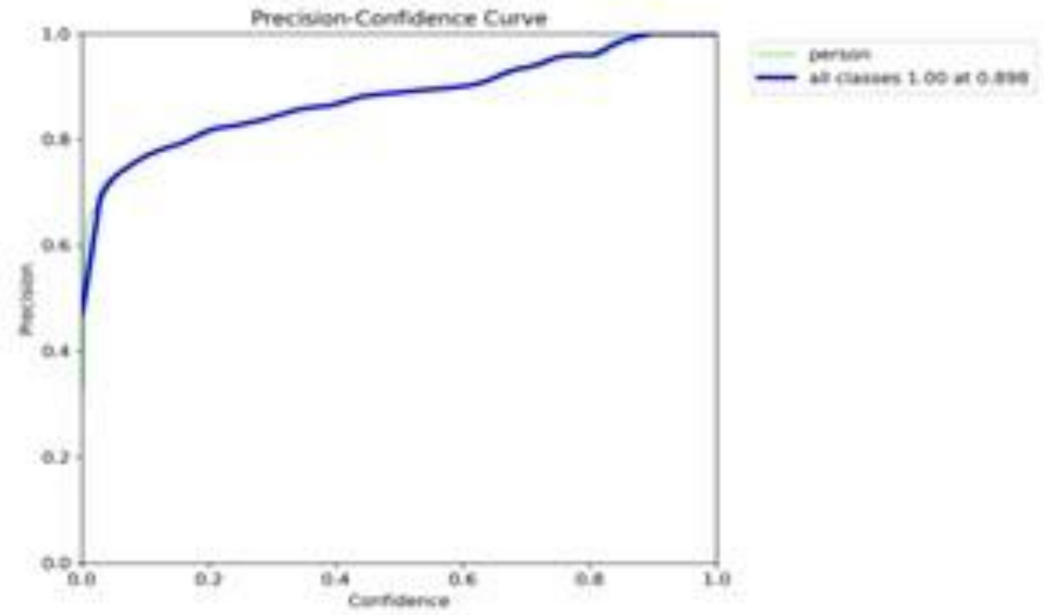

Figure 3. Precision-confidence curve

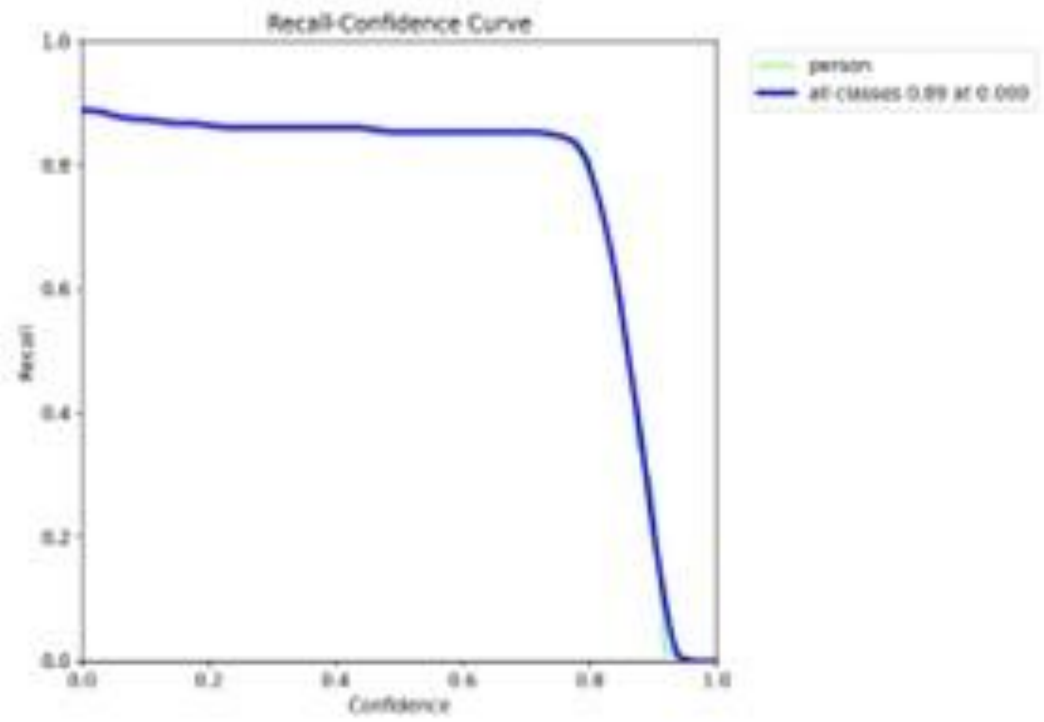

Figure 4. Recall-Confidence Curve

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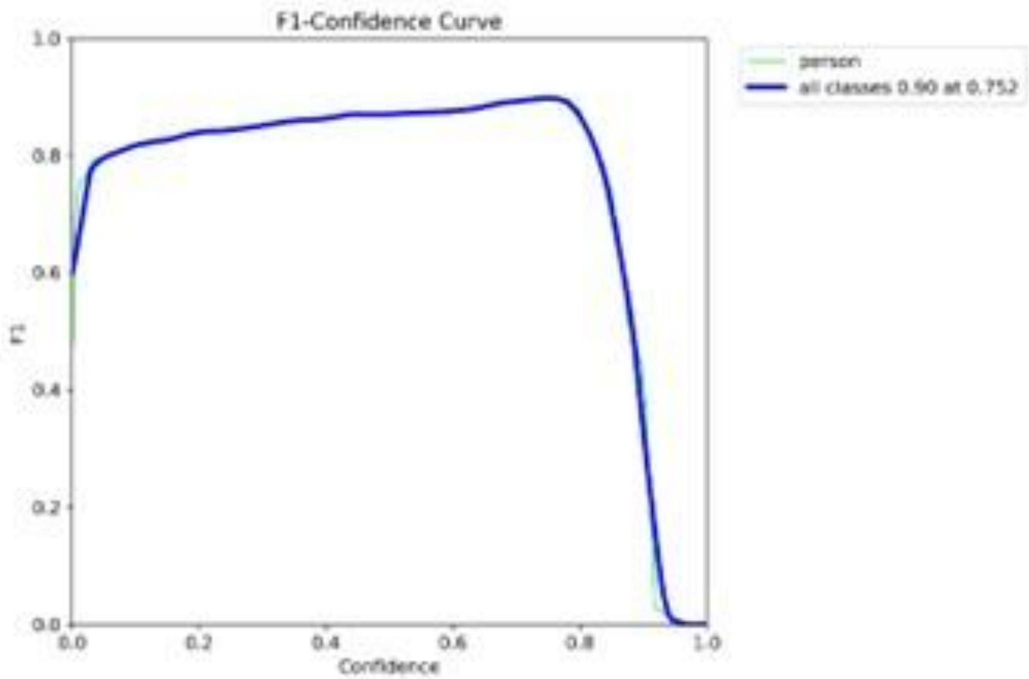

Figure 5. F1-Confidence Curve

4.1.5 Calculation of Confusion Matrix

The following steps explain how to calculate confusion matrix:

1. Define Classes: Each anatomical keypoint ("Nose," "Neck," "Shoulder L") is taken as an individual class for classification. All keypoints in the dataset should have consistent labeling.
2. Collect Predictions: Collect the keypoints predicted by the model of pose detection and their ground truth annotations from the dataset.
3. Apply Thresholding: Set the confidence level as a threshold to decide if the keypoint prediction is valid. For example, detect only those keypoints with confidence scores higher than some pre-defined threshold (say, 0.5); reject the rest. This step will minimize the contribution of low-confidence predictions and, hence, some clutter of noisy predictions.
4. Create Confusion Matrix: Compare predicted keypoints for the ground truth keypoints. For each keypoint: True Positive (TP),False Positive (FP), False Negative (FN),and True Negative (TN). Count these metrics for each class of keypoint. By doing this, you will build up the matrix and be able to see on a granular level performance by class, as well as where to focus effort for improvement.

4.1.6 Performance Metrics

The model was validated based on standard machine learning evaluation metrics to assess its ability to classify ergonomic postures effectively... Key performance metrics support YOLOv11 model ergonomic assessment Key performance metrics underscore the robustness of the YOLOv11 model in ergonomic assessment within OR environments: mAP 94.5%,represents high precision in detecting joint positions; having a rate of 95.0% of postures correctly detected legitimizes high-reliability posture correctness identification; a recall of 84.7% describes high sensitivity to changes in posture and good detection of ergonomic risks; and an F1-score, circa 89.5, balances a little more on the side of precision. Hence, these results reflect the ability of YOLOv11 to maintain high accuracy and low error rates, even in complex, occlusion-heavy OR conditions; hence, it is considered a powerful tool for real-time ergonomic monitoring.

To comprise our model YOLOv11 with OpenPose and MediaPipe. We test and train each model on the same annotated dataset. Table 1 indicates the comparative results of the three models of pose estimation—namely OpenPose, MediaPipe, and YOLOv11—in terms of their ability to detect ergonomic risk factors in a surgical environment. Of the three models, YOLOv11 produced the highest overall

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performance. It yielded a mean Average Precision value amounting to 94.5%, with a score of precision as high as 95% and an F1-score of 89.5%, which greatly outstripped the other two, OpenPose and MediaPipe. The

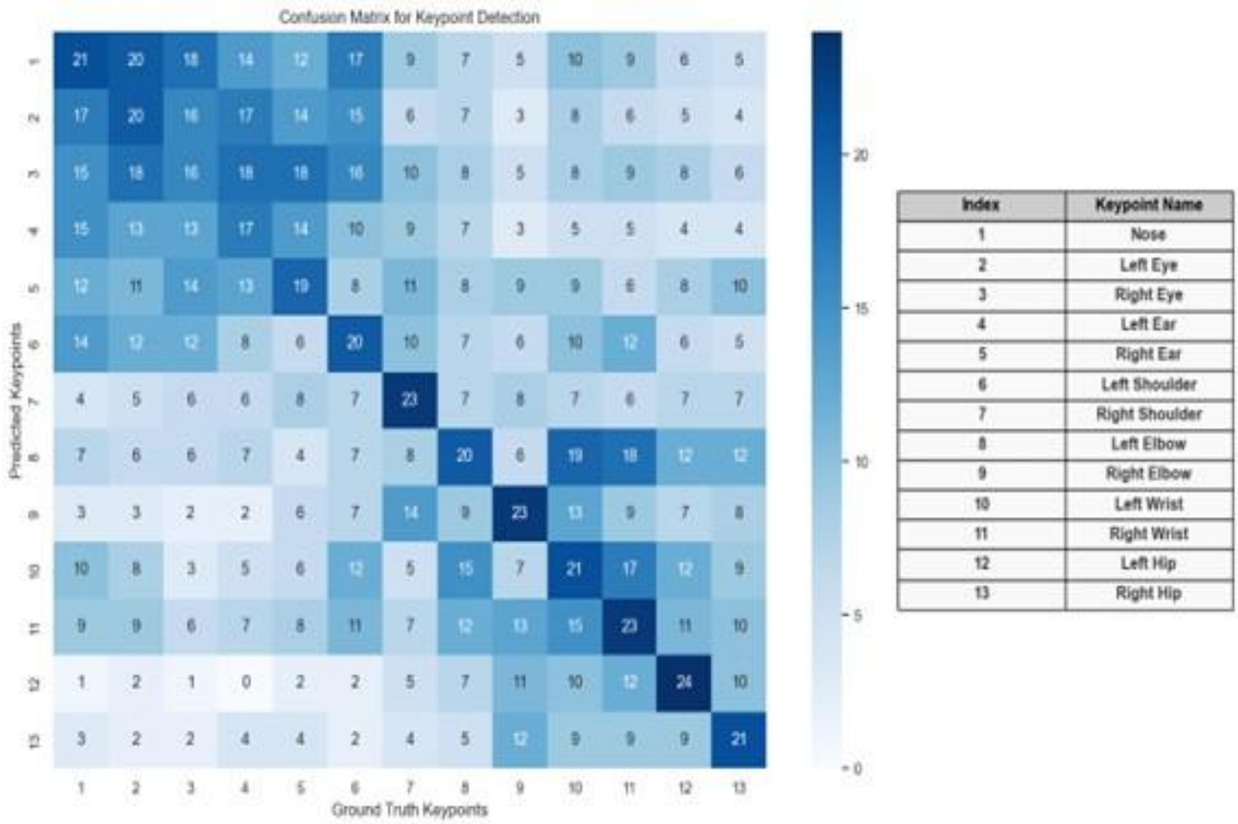

Figure 6. Confusion Matrix for Keypoint Detection: This matrix compares predicted keypoints to ground truth labels across
13 anatomical landmarks. The diagonal values represent accurate detections, while off-diagonal entries highlight misclassifications. The darker the shade, the higher the frequency of predictions for a given keypoint. The accompanying table provides keypoint indices and names for reference

Table 1. Performance Comparison of Pose Estimation Models

Model	mAP	Precision	Recall	F1-Score
OpenPose	65%	67%	70%	68%
MediaPipe	67%	66%	53%	60%
YOLOv11	94.5%	95%	84.7%	89.5%

high precision of YOLOv11 means that it can well determine postures of the body with very low false alarm probabilities. An 84.7% value of the recall score also means high sensitivity concerning the ergonomic risks, i.e., fewer miss false alarms of bad postures.

Here, OpenPose has attained 70% recall with an F1-score of 68%, reflecting the trade-off between precision, which is estimated to be 67%, and the recall. With much lower mAP at 65%, the accuracy is speaking to the challenge of detecting the posture keypoints. Another system, MediaPipe, performs a bit better than OpenPose judging by the mAP scores, having delivered 67%. Unfortunately, it seems to have compromised missed detection which stands at 53% hence giving a lower F1-score of 60%. This means that in an environment wherein poor postures are likely to be missed by the system, such as an intense and high-stakes operating room, MediaPipe will be less dependent on the system.

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Overall, the upgraded architecture of YOLOv11 as well as its occlusion-handling mechanisms speaks to its accuracy success in the ergonomic assessment, thereby making it the model that is most proper for carrying out real-time posture monitoring in surgical environments.

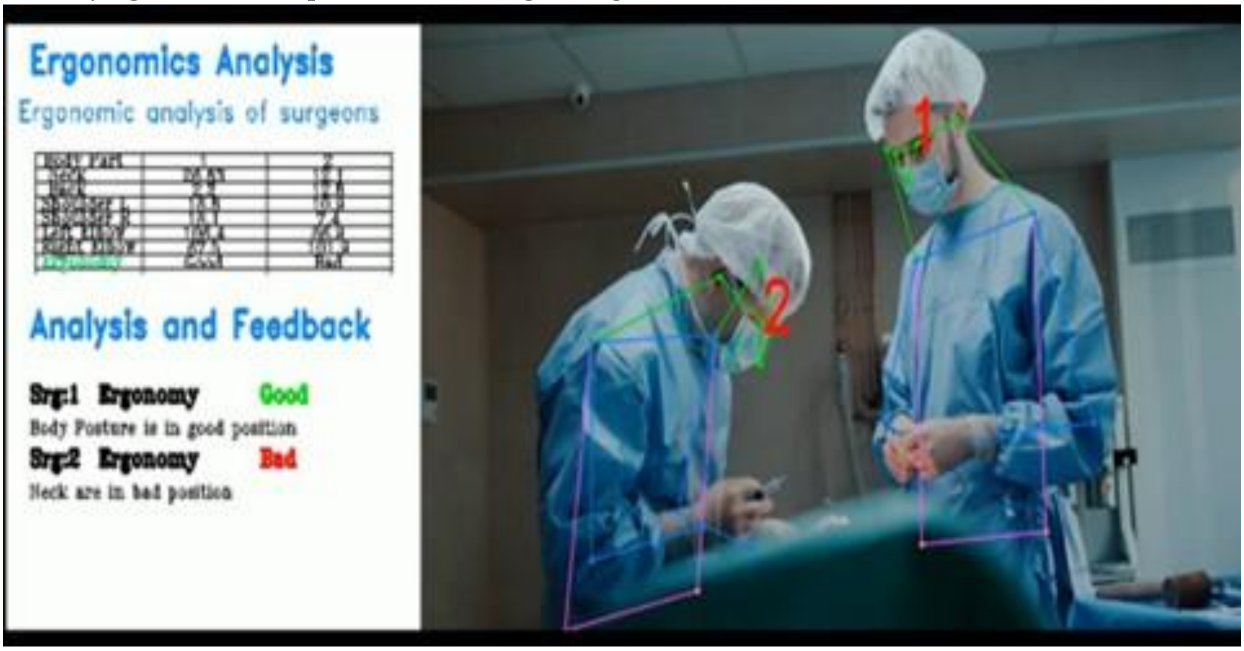

Figure 7. Real-time video feed showcasing detected keypoints and calculated angles, overlaid with color-coded posture alerts

4.2 Visual Output

4.2.1 Live Video Feed Display

The system will show in real-time the video feed coming from any surgical procedure with keypoints detected and angles calculated over it as shown in figure 7. Hence, surgeons can monitor their posture all the time in live applications during operations and give feedback to change ergonomics. The keypoints are annotated in the video feed, displaying the respective angles for immediate visual cues on posture (e.g., neck, shoulders, elbows).

4.2.2 Video Playback Interface

A playback interface for viewing recorded surgical videos, synchronized with posture analysis. The following features were supported for this:

1. Video Controls: Play, pause, slow motion, fast forward, and rewind functionalities for video navigation.
2. Overlaid Annotations: Keypoints and angles calculated from a video as it plays Surgeons/Trainers can pause the video and analyze a particular sequence in detail for post-operative analysis of the surgeon's posture and ergonomic compliance. It acts as a learning and assessment tool, through which one can identify what needs rectification regarding posture. This can be corrected in subsequent procedures.

4.2.3 Feedback Mechanism

To improve usability and the results achieved in ergonomics, the system uses a feedback mechanism:

1. Visual Alerts: Real-time Indicators of Ergonomic Posture via a Color-Coded System
2. Green: Good posture, meeting adequate ergonomic standards
3. Yellow: A moderate posture that requires some minor adoptions
4. Red: Bad posture adopts immediately to cancel ergonomic risks Text-Based Recommendations Displayed in Real-Time:
   Alongside Visual Alerts

4.2.4 Example Visual Representations

- Live Keypoint Overlay:

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- – Shows detected keypoints (e.g., neck, shoulders, elbows) overlaid on a live video feed with corresponding angles calculated and displayed.
- Annotated Video Playback:
- – Displays a recorded video with real-time posture analysis and color-coded alerts based on ergonomic assessment.
- Feedback Overlay:
- – Text-based and visual alerts (color-coded) highlight problematic postures with corrective suggestions.

5 CONCLUSION

This study integrates YOLOv11-based deep learning models into the real-time ergonomic posture analysis system in surgical environments. Such integration ensures that the model will efficiently detect the key postural landmarks, which are the neck, shoulder, back, and elbow, followed by immediate feedback to be received by the surgeon to help him maintain ergonomic postures throughout the operations.

Our results show that deep learning pose estimation models, like YOLOv11, can work well for real-time ergonomic monitoring in occlusion-heavy operating room (OR) environments. The self-attention mechanisms and anchor-free detection heads in YOLOv11 help strong joint detection even when surgical instruments and personnel partially obstruct key body parts.

A system that classifies postures into good, moderate, and high-risk categories based on the outcomes of calculations made from the angles of human joints, considering the ergonomic risk assessment frameworks RULA and REBA. Once validated, this system demonstrated high performance as mAP (94.5%), attesting to its trustability for ergonomic posture classification. The feedback loop inside the model will alert immediately when there are deviations in postures from the recommended ergonomic positions, hence lowering the risks of Muscular Skeletal Disorders (MSDs) for surgeons.

This model was validated based on 700 images annotated to generalize different surgical scenarios. This is the first-ever system that does not follow manual observation or self-report for ergonomic assessment. Rather, it provides a non-intrusive continuous monitoring approach. Ergonomic safety is therefore achievable without disruption to the surgical workflow. Perspective for improvements may include:

- Considering a bigger set of data composed of different types of surgeries as well as postural diversity.
- Adding multi-camera views or 3D body position calculation to improve covering up one body part by another.
- Putting in time tracing to study how posture changes over time, showing tiredness spotting in extended operations.

This work sets up YOLOv11 as an acceptable answer for quick comfortable check in surgery places, giving a base for later AI changes in health at work and surgery quality.

AUTHOR CONTRIBUTION ADDITIONAL INFORMATION

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Ethical Statement: This article contains no studies with human participants or animals performed by authors.

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