Approach for Postural Disorders Recognizing from Visual Data Using Deep Neural Network

Iurii Krak[1,2], Olexander Mazurets[3,*], Olha Zalutska[3], Maryna Molchanova[3,*] and Olexander Barmak[3]

[1] *Taras Shevchenko National University of Kyiv, Ukraine*
[2] *Glushkov Institute of Cybernetics of NAS of Ukraine, Kyiv, Ukraine*
[3] *Khmelnytskyi National University, Khmelnytskyi, Ukraine*

Abstract

In paper proposed approach to recognizing postural disorders from visual data based on analysis of anatomical landmarks coordinates of spine, determined using deep learning neural network. The quantitative model for assessing spinal curvature is proposed, which provides an interpreted representation of the spatial characteristics of posture. The calculated angular values allow identifying deviations from the norm in the spine geometry. Visualization of key points and their mutual position form the basis for explaining the model solutions. The method for recognizing postural disorders from visual data is developed for analysis of key anatomical landmarks of the spine, determined using deep neural network. Using the coordinates of key points (cervical, thoracic, lumbar and sacral spine), the method assesses the spine curvature and determines deviations from the norm, which allows identifying pathological changes, such as hyperlordosis, hyperkyphosis or scoliosis. The method integrates geometric analysis with threshold-based classification procedure, which makes it possible to apply it in automated posture control tasks. The research is aimed at resolving the contradiction between the need for accurate posture analysis and the requirements for the availability and ease of use of appropriate technological solutions: traditional hardware provides high accuracy, but limits scalability due to the high cost and operation complexity. The proposed method is based on visual data analysis and does not require specialized equipment. This allows to reduce the barriers to implementation and at the same time provide an interpretable assessment of posture, which demonstrates the possibility of eliminating the specified contradiction by using computer vision and explanatory artificial intelligence models. The general problem of determining the presence of posture disorders is solved by the developed method with Accuracy 0.86, in conditions of different image quality, two-dimensional nature of analysis and fixed body orientation.

Keywords

postural disorders, posture control, visual data analysis, image recognizing, deep neural network

1. Introduction

In the current conditions of rapid development of digital technologies and global digitalization of society, there is a growing need for the implementation of intelligent systems for monitoring the physical condition of a person in real time [1, 2]. One of the urgent tasks in this direction is the early detection of posture disorders, which is of significant importance not only for the prevention of musculoskeletal diseases, but also for improving the quality of life of the population, especially

Workshop "Intelligent information technologies" UkrProg-IIT`2025 co-located with 15th International Scientific and Practical Programming Conference UkrPROG'2025, May 13-14, 2025, Kyiv, Ukraine
* Corresponding author.
yuri.krak@gmail.com (I. Krak); exe.chong@gmail.com (O. Mazurets); zalutsk.olha@gmail.com (O. Zalutska); m.o.molchanova@gmail.com (M. Molchanova); alexander.barmak@gmail.com (O. Barmak)
0000-0002-8043-0785 (I. Krak); 0000-0002-8900-0650 (O. Mazurets); 0000-0003-1242-3548 (O. Zalutska); 0000-0001-9810-936X (M. Molchanova); 0000-0003-0739-9678 (O. Barmak)

in the context of urbanization, the growth of a sedentary lifestyle and the aging of the population [3, 4].

Human posture is a complex biomechanical characteristic, changes in which can affect the effectiveness of physical activity, productivity and overall comfort. In this regard, the tasks of detecting postural deviations are gaining particular relevance in the context of the development of automated surveillance systems, ergonomic solutions for the office environment, adaptive learning platforms and smart spaces [5, 6]. Deep neural networks provide a high level of accuracy in detecting posture features even under difficult shooting conditions or various anatomical features of the user [7, 8].

The development of such technologies is closely related to the Sustainable Development Goals, in particular Goal 9 - "Industry, Innovation and Infrastructure", which focuses on the introduction of digital innovations into various spheres of life [9]. The creation of adaptive intelligent systems for analyzing human posture contributes not only to improving the quality of the living environment, but also to the formation of new approaches to the interaction between humans and digital systems in smart cities, educational institutions and production processes [10].

The aim of the paper is to develop an intelligent method for automated detection of human posture disorders from visual data by analyzing the spatial coordinates of key anatomical landmarks of the spine, which are identified using deep neural network. The main focus is on developing a quantitative model that provides an interpreted assessment of spinal curvature based on anatomically significant landmarks, reflecting the principles of explainable artificial intelligence. The calculated angular values, as well as the visualization of key points in the image, create a transparent space for analysis, allowing the user to trace the cause-and-effect relationship between the spatial arrangement of spinal elements and the model's decision on the presence of posture disorders. This approach increases the level of confidence in the system and supports the interpretation of results in a practical context.

The contributions of the paper are the applied implementation of a formalized approach to assessing human posture based on the coordinates of four key points along the spine with subsequent calculation of angles between the corresponding segments. The proposed methodology combines biomechanical interpretation of spatial data with a neural network image analysis architecture, allowing the identification of both general and specific postural disorders. In addition, the model offers an integrated decision-making system based on threshold deviations, which increases the reliability of diagnostics and opens up opportunities for its application in automated ergonomic support systems, educational and sports environments.

2. Related works

The problem of detecting postural disorders is integrated into the broader context of human posture analysis tasks, which is an active research area in the field of computer vision and biomechanics [11]. The task of automated posture assessment, in particular the identification of its disorders, is attracting increasing attention of the scientific community, as it combines the need for high-precision analysis of anatomical structures with the use of modern artificial intelligence methods [12]. In this context, modern approaches to determining human postures and specialized solutions aimed at detecting postural anomalies deserve consideration.

The study [13] is devoted to the development of machine learning models for classifying human sitting posture, collected using two 32x32 pressure sensors installed on the seat and back of a chair. The main goal is to identify incorrect sitting habits that can lead to back pain and musculoskeletal diseases, especially among the elderly, people with disabilities and office workers. Five machine learning algorithms were used: Random Forest, Gaussian Naïve Bayes, Logistic Regression, Support Vector Machine, and Deep Neural Network. The KFold cross-validation technique was used to evaluate the models. The results showed high average classification accuracies: 98% on the control dataset and 97% on the realistic dataset, for six sitting postures.

The work [14] is also devoted to solving the problem of detecting incorrect sitting postures through posture recognition in robotic systems. This is an important problem due to the negative impact of prolonged stay in incorrect postures on health, in particular the development of spinal diseases and myopia. Existing methods of posture recognition are mostly focused on identifying the features of the human body, but do not take into account the surrounding objects in the scene, which limits their ability to detect some types of incorrect sitting postures, especially in difficult conditions. To solve these problems, the authors propose an approach that combines scene recognition and semantic analysis to detect incorrect sitting postures. For this purpose, the Microsoft Kinect sensor is used, which tracks key points of the human skeleton, and the Faster R-CNN deep learning method is used to accurately recognize objects in the scene. Next, the system performs semantic analysis using behavior clustering based on Gaussian mixture models for better understanding of the scene. By combining the detected features of the skeleton and the objects of the scene, the method allows you to accurately distinguish between different sitting postures. Experimental results showed that this approach not only detects more types of incorrect sitting postures than existing methods, but also avoids errors in complex environments. This approach has the potential to be integrated into robotic healthcare and treatment systems, improving posture monitoring and treatment processes.

The study [15] considers a system for non-contact recognition of sitting postures of office workers using various health classification methods. Poor sitting postures are often associated with the development of musculoskeletal disorders, so it is important to assess healthy sitting postures. The work defines five sitting postures based on medical literature and standards. Thirty participants held these postures for 30 seconds, while posture data were recorded using a Kinect device. To overcome difficulties such as desks and computers, two datasets with different joint points were created. The pose markers were defined by calculating the angles between body parts such as legs, hips, and back. Various methods were used for classification, including neural networks, Support Vector Machine (SVM), K-Nearest Neighbors, Naive Bayes, AdaBoost, decision tree, Random Forest and Ensemble Learning (EL). The highest accuracy was achieved using EL and SVM – 99.8% and 99.7%, respectively. The first and fifth postures were found to be the most comfortable. The aim of this system is to improve sitting behavior and its use for health monitoring and robotic vision.

The study [16] presents a Smart-Cover system that automatically monitors sitting posture to prevent health problems, including back pain and spinal deformities, that can occur due to prolonged sitting in asymmetrical postures. Traditionally, subjective observation methods by experts or expensive laboratory motion capture systems, which are not always available, are used to assess posture. This study proposes a more accessible and cost-effective approach based on the use of a Seat Pressure Sensor (SPS), consisting of Velostat materials, conductive fabric, and foam to collect information about the pressure distribution on the seat surface. Pressure data is collected from 10 healthy young adults, each of whom sits for 30 minutes. The information is transmitted to a cloud server using the Internet of Things (IoT), which allows for real-time posture monitoring. A rule-based classifier is used to process the data, providing the user with notifications about the duration of sitting and the level of asymmetry. A new application for end devices was developed that displays the level of asymmetry of the seat, as well as information about active and static sitting, along with the final results for the day.

In the paper [17], a system for recognizing the position of the sitting posture is presented, which is based on the use of 15 pressure-sensitive sensors embedded in the seat. The system is connected to a peripheral computing device that provides the operation of a convolutional neural network to classify eight types of sitting postures. A dataset with time series of signals from all 15 sensors for each of the postures was collected for training the model. The proposed CNN model was found to be more effective than SVM, KNN, ANN and the combined CNN+LSTM model, providing accurate recognition of sitting postures based on spatiotemporal features.

In [18], a new model of a deep recurrent hierarchical network (DRHN) based on MobileNetV2 is proposed for human posture detection. The model allows to reduce or eliminate problems associated with limited visibility of the human torso in the frame, in particular the problem of occlusion. DRHN processes sequences of RGB-Depth frames and generates representations of semantically related posture states. The results showed an accuracy of 91.47% in recognizing the sitting posture at a frequency of 10 frames per second.

The authors [19] proposed a new approach for human posture recognition using FMCW radar, which allows determining the poses of two people in close proximity. Using data on distance, speed and angle obtained by the radar, point clouds are derived in a Cartesian coordinate system. Then, unsupervised clustering methods are used to separate people, as well as the DenseNet deep learning model to classify their poses. Four basic poses are recognized: standing, sitting on a chair, sitting on the floor and lying down, as well as ten combinations of poses for two people with an accuracy of up to 96%. Experiments with five combinations of poses of two overlapping people showed an accuracy of over 96%.

When analyzing known works in the direction of research on the detection of human posture disorders, most of the works use additional devices: pressure sensors, Kinect, depth sensors or special seats. This complicates the scaling of solutions, limits their use in home or office environments without special infrastructure. Also, some approaches require physical contact or very close proximity of sensors to the body, which reduces user comfort and limits long-term use. Some solutions are based on neural networks without clear visualization of the reasons for the classification (why the pose is recognized as correct/incorrect), which makes it difficult to trust the AI solution.

3. Approach for recognizing postural disorders from visual data

On the one hand, effective detection of postural disorders requires highly accurate spatial information about the body position, which is usually provided by hardware (pressure sensors, depth cameras, specialized chairs), which allows obtaining reliable and accurate results [20, 21]. On the other hand, the widespread implementation of such solutions is limited by their cost, complexity of use, the need for physical contact or specific data collection conditions, which reduces their accessibility for the mass user [22].

Thus, a contradiction arises between the need for highly accurate, reliable and interpretable analysis of posture and the need to create inexpensive, easy-to-use and accessible solutions that do not require specialized equipment.

The proposed approach – building an interpreted model of detecting postural disorders based on visual data – is aimed at overcoming this contradiction through a combination of computer vision methods and explanatory artificial intelligence.

3.1. Formalization of approach for recognizing postural disorders from visual data

Within the work scope, 4 key points along human spine will be used to detect human posture disorders based on visual data: Cervical Spine, Thoracic Spine, Lumbar Spine, Sacral Spine.

Let the set of points P characterize the posture of a person in the photo:

$$P=\{(x_1, y_1), (x_2, y_2), (x_3, y_3), (x_4, y_4)\} \tag{1}$$

Accordingly, (x_1, y_1) is a point belonging to the cervical spine, (x_2, y_2) is a point belonging to the thoracic spine, (x_3, y_3) is a point belonging to the lumbar spine, and (x_4, y_4) is a point belonging to the sacral spine. This set of points allows us to describe the main curvatures of the spine and determine the type of posture disorder based on their coordinates and mutual angles are sufficient to detect posture disorders, since they correspond to the key anatomical landmarks of the spine that determine its curves [23].

The human spine in a normal state has four main curvatures: cervical lordosis (forward curvature), thoracic kyphosis (backward curvature), lumbar lordosis (forward curvature), and sacral kyphosis (backward curvature) [24]. The described points cover these departments, which allows us to assess deviations from normal posture.

Posture is determined by the relative location of these points and their angles of inclination. The main curves of the spine can be characterized by three angles (2, 3, 4) between the corresponding segments of spine. Cervical angle (θ_1) – between cervical and thoracic regions:

$$\theta_1 = arctan((y_2 - y_1)/(x_2 - x_1)) \tag{2}$$

Thoracic angle (θ_2) – between the thoracic and lumbar regions:

$$\theta_2 = arctan((y_3 - y_2)/(x_3 - x_2)) \tag{3}$$

Lumbar angle (θ_3) – between the lumbar and sacral regions:

$$\theta_3 = arctan((y_4 - y_3)/(x_4 - x_3)) \tag{4}$$

These angles will be compared to normal reference values (θ_1^*, θ_2^*, θ_3^*) to detect deviations. The deviation function will be used to assess posture:

$$\Delta\theta_i = \theta_i - \theta_i^*, \ i=1,2,3 \tag{5}$$

where i – the ordinal number of the angle from views 2 – 4.

If at least one of $\Delta\theta_i$ exceeds the permissible value ε, then a posture disorder is present:

$$\text{The disorder is detected} \Leftrightarrow \exists\, i \text{ such that } \Delta\theta_i > \varepsilon_i, \tag{6}$$

where ε_i – the permissible deviation of the i-th angle, established empirically.

The type of posture disorder is proposed to be determined by the signs of $\Delta\theta_i$. Accordingly, hyperlordosis (excessive forward bending) can then be formalized as follows:

$$\theta_1 > \theta_1^* \text{ and } \theta_3 > \theta_3^*, \tag{7}$$

Hyperkyphosis, or excessive backward bending, is suggested to be detected as follows:

$$\theta_2 > \theta_3^*, \tag{8}$$

A flat back, or the absence of natural curves, is suggested to be identified as follows:

$$\theta_1 \approx \theta_1^* \text{ and } \theta_2 \approx \theta_2^* \text{ and } \theta_3 \approx \theta_3^*, \tag{9}$$

Scoliosis, or lateral curvature, is proposed to be defined as the deviation of the coordinates of abscissa axis:

$$|x_2 - x_1| > d_1 \text{ or } |x_3 - x_2| > d_2, \tag{10}$$

where d_1, d_2 are critical displacement values determined empirically.

Then the normality of posture can be defined as the normalized sum of deviations:

$$S = \sum_{i=1}^{n} \frac{\Delta\theta_i}{\theta_i^*}, \tag{11}$$

If $S<\lambda$, then the posture is considered normal, otherwise it is considered that there is a violation. Where λ is an empirically established threshold, n is the total number of angles corresponding to the representations (2) – (4), in this study n=3 used.

Therefore, the proposed model allows to quantitatively assess the posture of a person based on the key points of the spine, analyzing the angles between them. It is based on determining the normal reference values of the angles and comparing them with the real coordinates.

3.2. Method for recognizing postural disorders from visual data via deep neural network

The method for recognizing postural disorders from visual data via deep neural network is based on the analysis of key anatomical landmarks of the spine, determined using a neural network. Using the coordinates of key points (cervical, thoracic, lumbar and sacral spine), the method assesses the curvature of the spine and determines deviations from the norm, which allows identifying pathological changes, such as hyperlordosis, hyperkyphosis or scoliosis. The steps of the method are shown in Figure 1.

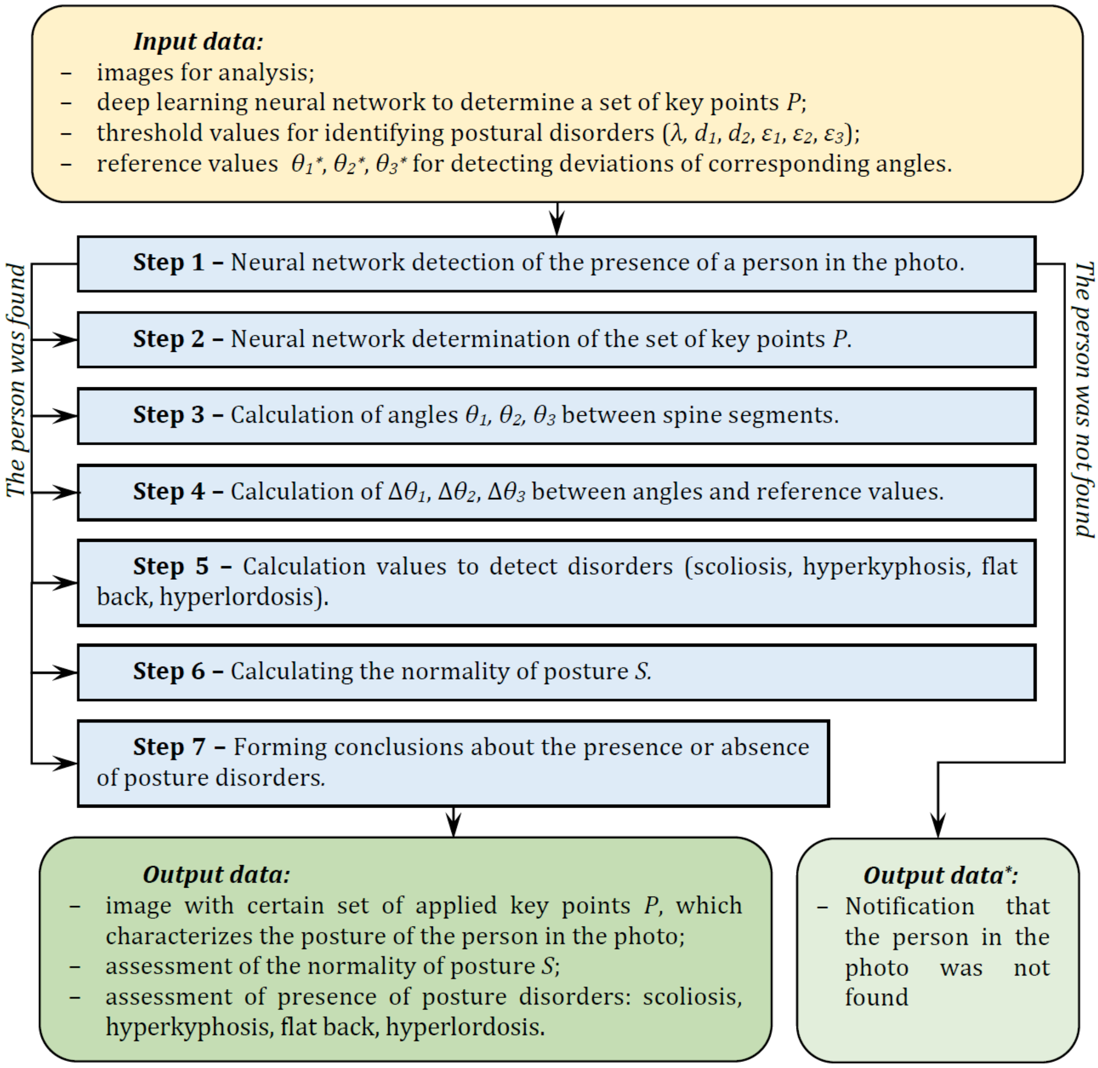

Figure 1: Steps of the method for recognizing postural disorders from visual data.

The input data of the method are images for analysis, a deep learning neural network («YOLO11s-pose» model) for determining the set of key points P, threshold values for identifying posture (λ, d_1, d_2, ε_1, ε_2, ε_3) and reference values θ_1^*, θ_2^*, θ_3^* for detecting deviations of the corresponding angles between the corresponding segments of the spine.

In step 1, the neural network determines the presence of a person in the photo. If person in photo is identified, steps 2-7 are performed, if not identified, transition to original data occurs.

Step 2 performs the neural network determination of the set of key points P, which will subsequently be used to calculate the angles between the segments of the spine (step 3), according to representations (2) – (4).

In step 4, $\Delta\theta_1$, $\Delta\theta_2$, $\Delta\theta_3$ between the angles and reference values are calculated according to the representation (5), and in step 5, the values for detecting scoliosis, hyperkyphosis, flat back, hyperlordosis are calculated according to the representations (7) – (10).

Step 6 calculates the normality of posture S according to the representation (11). Step 7 summarizes all steps and forms conclusions about presence or absence of posture disorders.

The initial data is an image with a certain set of applied key points P, which characterizes the posture of a person in the photo; assessment of the normality of posture S and assessment of the presence of posture disorders: scoliosis, hyperkyphosis, flat back, hyperlordosis.

The proposed method of intellectual detection of human posture disorders from an image provides a quantitatively justified approach to diagnosing spinal deformities by analyzing the spatial coordinates of four key anatomical points that reflect the main physiological curvatures of the back. Based on the calculation of the angles between the spinal segments and their comparison with reference values, the method allows to detect both general postural disorders and specific pathologies, in particular hyperlordosis, hyperkyphosis, flat back and scoliosis. Its integration with a neural network provides automated localization of key landmarks in the image, which makes it possible to fully automatically assess the state of posture without the need for manual intervention, as well as visual presentation [25] of the results of the assessment of the state of posture. Thus, the method serves as a reliable basis for creating posture monitoring systems in medical, sports and educational environments, contributing to the early detection of deviations and reducing the risks of developing chronic diseases of the musculoskeletal system.

3.3. Research dataset

To fine-tune the deep learning model for task of determining keypoints from set P, dataset «Posture Keypoints Detection – Photos & Labels» [26] from the Kaggle platform was selected.

The dataset is intended for computer vision and machine learning tasks, focusing on studying the posture of people leading a sedentary lifestyle. It contains images of people in a sitting or standing position, with additional annotations indicating keypoints of the body in the YOLO pose format. These annotations include the coordinates of important markers (from the set P) that help determine the position of the person in the image. The dataset was checked for class balance [27]. The dataset consists of 250 annotated files for training and 50 annotated files for validation.

The YOLO11s-pose model [28] uses an adapted version of the YOLO architecture for the pose recognition task. It is trained on large datasets of human poses, where labels indicate the location of key points of the body, such as shoulders, elbows, knees, as well as points on the spine and joints. Thanks to this, the model is able to detect these key points even in complex images with different backgrounds and lighting variations, making it very suitable for posture analysis.

4. Experiment

To conduct the experiment, an application software implementation was performed in the Google Colab cloud environment [29] using the Python language [30, 31]. The «v2-8 TPU» runtime environment was used – the server part (TPU) for Python 3 Google Compute Engine with 334.6 GB of system RAM and 225.3 GB of disk space.

The software implementation consists of 2 main modules – the «YOLO11s-pose» fine-tuning module and the module for detecting postural disorders from visual data. The fine-tuning module is designed to train a neural network for the tasks of detecting a person in an image and finding key points.

The module for detecting postural disorders uses a finely tuned neural network for automated detection of a person in a photo and marking key points of the spine, which are used for the analysis described in Section 3. An example of the operation of the posture disorder detection module is shown in Figure 2 (a photo from the dataset [26] is analyzed).

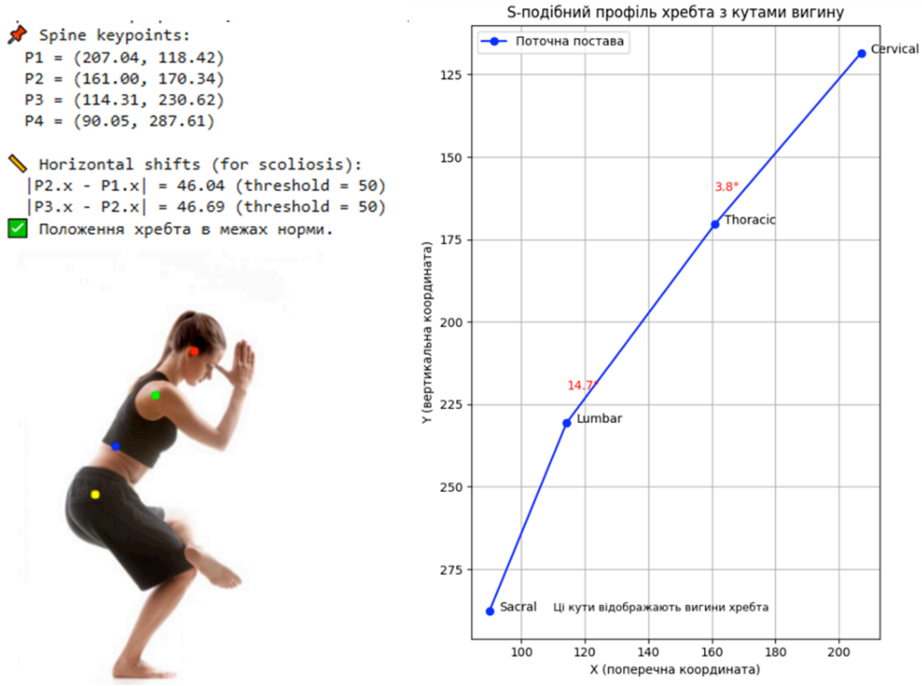

Figure 2: Example of posture disorder detection.

Using the developed experimental software for postural disorders recognizing from visual data using deep neural network, the results described in the following section were obtained.

5. Result and discussion

The neural network for detecting key points of the spine was trained for 50 epochs. The graphs with the training results are shown in Figure 3.

The graphs demonstrate the typical dynamics of the YOLO model training with error labels and quality metrics. Overall, the training looks efficient and balanced, with a gradual decrease in the losses on the training and validation choices, as well as a steady increase in the metric accuracy, recall, and mean accuracy (mAP) for objects (*B*) and poses (*P*).

There is a clear trend towards training losses without sharp fluctuations, indicating stable training. The validation losses also decrease, albeit with minor peaks.

All key metrics (Precision, Recall, mAP) are steadily increasing and show progress even towards the end of training. In particular, mAP50-95(P) has not yet reached plateau, indicating potential for further improvement [32]. Given current trajectory of the metrics, it is advisable to continue training to squeeze out additional quality, especially in the pose and mAP parts. However, due to lack of computing units, this could not be verified at this stage in research.

According to the graphs in Figure 3, the model demonstrates satisfactory keypoint detection quality: mAP@0.5 for poses (*P*) reaches approximately 0.75, indicating high localization accuracy at a moderate threshold, while the more stringent mAP@0.5:0.95 indicator is approximately 0.45, indicating a decrease in accuracy when taking into account a larger IoU range. The metrics precision(P) and recall(P) approach 0.7 and 0.65, respectively, confirming the stable, although not ideal, ability of model to accurately and completely detect key points.

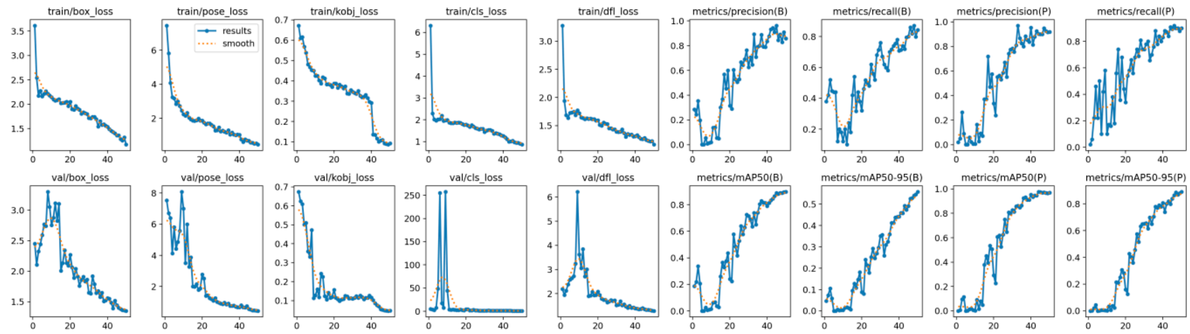

Figure 3: Neural network «YOLO11s-pose» training result.

The ability of the created application software implementation to detect posture disorders was also tested. An example of posture disorder identification is shown in Figure 4 (a photo from the dataset [26] is analyzed by software).

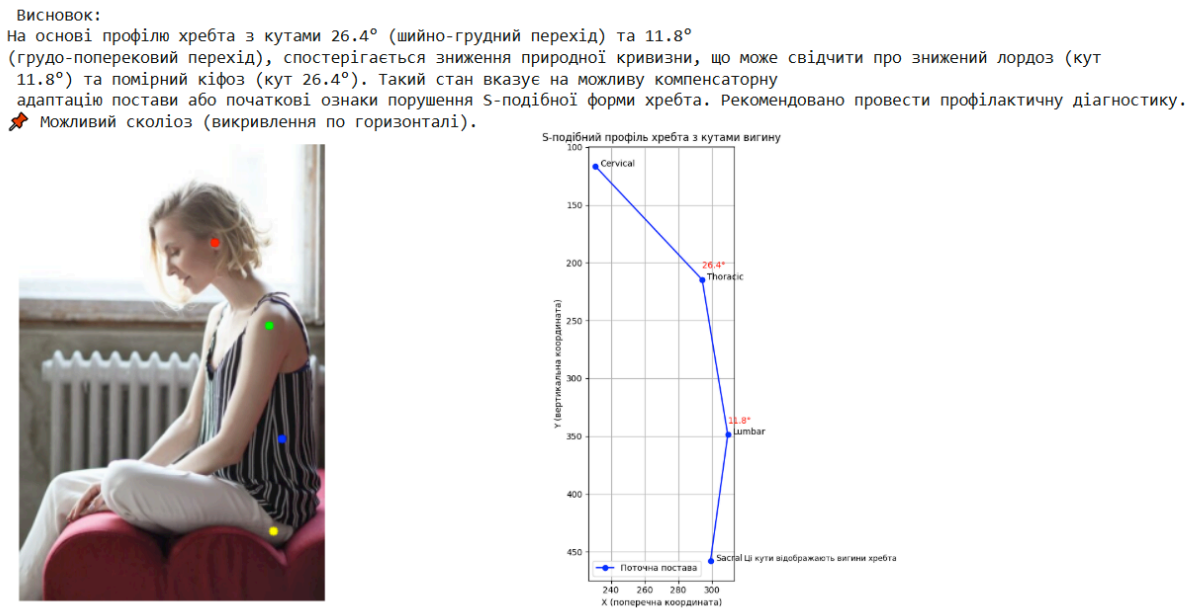

Figure 4: Detection of posture disorders by developed software.

The conclusions made by the developed software are fully consistent with the conclusions of experts. In binary classification of images with and without posture disorders, the proposed approach gave Accuracy 0.86 (43 out of 50 images were classified correctly). Such accuracy is due to the fact that in 5 images it was not possible to identify a person, and in 2 more it was not possible to identify all key points. that most of errors were not related to the logic of analysis, but to the impossibility of identifying a person or individual key points in some images.

It is important to note that the proposed solution does not require any physical sensors, markers or additional equipment, which makes it convenient, accessible and suitable for wide practical application, in particular in educational, sports and medical contexts.

Despite the effectiveness and convenience of the proposed approach, it has a number of limitations that should be taken into account in its practical application. First of all, the accuracy of the analysis depends on the quality of the image: blurry, darkened or too complex backgrounds can make it difficult to identify a person or key points. In addition, the method is two-dimensional and does not take into account the depth or three-dimensional geometry of the body, which can limit its accuracy when assessing more complex postural disorders. Another limitation is the fixation of the body in the frontal or lateral projection – body rotations, asymmetries or partially covered parts of the body can lead to errors in detection.

Future research directions will be aimed at increasing the accuracy and versatility of the proposed approach. In particular, the transition to three-dimensional posture analysis is promising, which will allow for more accurate detection of complex deformations and asymmetries, especially in the frontal projection.

6. Conclusion

In paper proposed approach to recognizing postural disorders from visual data based on analysis of anatomical landmarks coordinates of spine, determined using deep learning neural network. The quantitative model for assessing spinal curvature is proposed, which provides an interpreted representation of the spatial characteristics of posture. The calculated angular values allow identifying deviations from the norm in the spine geometry. Visualization of key points and their mutual position form the basis for explaining the model solutions. The method for recognizing postural disorders from visual data using deep neural network is developed based on the analysis of key anatomical landmarks of the spine, determined using a neural network. Using the coordinates of key points (cervical, thoracic, lumbar and sacral spine), the method assesses the spine curvature and determines deviations from the norm, which allows identifying pathological changes, such as hyperlordosis, hyperkyphosis or scoliosis. The method integrates geometric analysis with threshold-based classification procedure, which makes it possible to apply it in automated posture control tasks.

The research is aimed at resolving the contradiction between the need for accurate posture analysis and the requirements for the availability and ease of use of appropriate technological solutions: traditional hardware provides high accuracy, but limits scalability due to the high cost and operation complexity. The proposed method is based on visual data analysis and does not require specialized equipment. This allows to reduce the barriers to implementation and at the same time provide an interpretable assessment of posture, which demonstrates the possibility of eliminating the specified contradiction by using computer vision and explanatory artificial intelligence models.

To solve the problem of determining the key anatomical landmarks of the spine, the use of the «Posture Keypoints Detection» dataset from the Kaggle platform was justified, which contains annotated images of people in sitting and standing position. The "YOLO11s-pose" neural network model, adapted for pose recognition tasks, was used to process the data, which provides the key points detection. The developed method allows detecting key points along the human spine, which indicates the suitability of the selected neural network architecture for accurate and stable determination of the spatial position of anatomical landmarks necessary for further analysis of posture. The general problem of determining the presence of posture disorders is solved by the developed method with Accuracy 0.86, in conditions of different image quality, two-dimensional nature of analysis and fixed body orientation. The reduction in the estimate is affected by the errors of the neural network in identifying key points along the human spine. Complex backgrounds, turns or partial overlap also reduce the accuracy. Further research is aimed at implementing three-dimensional analysis to improve the detection of deformations and asymmetries.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

References

[1] C. Dong, G. Du, An enhanced real-time human pose estimation method based on modified yolov8 framework, Scientific Reports 14 (2024) 8012. doi:10.1038/s41598-024-58146-z.

[2] Z. Jiang, Z. Zhou, L. Li, W. Chai, C.-Y. Yang, J.-N. Hwang, Back to optimization: Diffusion-based zero-shot 3d human pose estimation, in: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2024, pp. 6142–6152.

[3] S. Mehraban, V. Adeli, B. Taati, Motionagformer: Enhancing 3d human pose estimation with a transformer-gcnformer network, in: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV), 2024, pp. 6920–6930.

[4] D. Udayan J, J. TV, R. Raman, H. Kim, P. Nedungadi, et al., Deep learning in monocular 3d human pose estimation: Systematic review of contemporary techniques and applications, Multimedia Tools and Applications (2025) 1–37. doi:10.1007/s11042-024-20495-2.

[5] X. An, L. Zhao, C. Gong, N. Wang, D. Wang, J. Yang, Sharpose: Sparse high-resolution representation for human pose estimation, in: Proceedings of the AAAI Conference on Artificial Intelligence,volume 38, 2024, pp. 691–699. doi:10.1609/aaai.v38i2.27826.

[6] J. Wu, Y. Wang, J. Liu, B. Zhu, X. Wang, L. Cao, H. Zhang, Research on driver posture recognition and prediction in vehicle, Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering 239 (2025) 796–808. doi:10.1177/09544070231209348

[7] W. Li, M. Liu, H. Liu, T. Guo, T. Wang, H. Tang, N. Sebe, Graphmlp: A graph mlp-like architecture for 3d human pose estimation, Pattern Recognition 158 (2025) 110925. doi:https://doi.org/ 10.1016/j.patcog.2024.110925.

[8] L. Yan, Y. Du, Exploring trends and clusters in human posture recognition research: An analysis using citespace, Sensors 25 (2025) 632. doi:10.3390/s25030632.

[9] W. H. Organization, World health statistics 2024: monitoring health for the SDGs, sustainable development goals, World Health Organization, 2024.

[10] Z. Gao, J. Chen, Y. Liu, Y. Jin, D. Tian, A systematic survey on human pose estimation: upstream and downstream tasks, approaches, lightweight models, and prospects, Artif. Intell. Rev. 58.3 (2025). doi:10.1007/s10462-024-11060-2.

[11] S. Bhattacharya, M. Sinha, V. Dutot, S. Akter, V. Venkatesh, Artificial intelligence, digitization, sustainable development goals & global disruptions, 2025. doi:10.1016/j.jjimei.2025.100334

[12] M. A. A. Baig, J. Huang, J. Xu, Ai for united nations sustainable development goals: Ai for unsdgs (2024). doi:10.31224/3866.

[13] T. A. Gelaw, M. T. Hagos, Posture prediction for healthy sitting using a smart chair, in: M. L. Berihun (Ed.), Advances of Science and Technology, Springer International Publishing, Cham, 2022, pp. 401–411. doi:10.1007/978-3-030-93709-6_26.

[14] W. Min, H. Cui, Q. Han, F. Zou, A scene recognition and semantic analysis approach to unhealthy sitting posture detection during screen-reading, Sensors 18 (2018) 3119. doi:10.3390/s18093119.

[15] H. Coskun, A Contactless Real-Time System to Classify Multi-Class Sitting Posture Using Depth Sensor-Based Data, y: Advances in Healthcare Information Systems and Administration, IGI Global, 2024, c. 333–368. doi:10.4018/979-8-3693-7277-7.ch011.

[16] A. R. Anwary, D. Cetinkaya, M. Vassallo, H. Bouchachia, et al., Smart-cover: A real time sitting posture monitoring system, Sensors and Actuators A: Physical 317 (2021) 112451. doi:10.1016/ j.sna.2020.112451.

[17] Y. Gupta, Y. Goyal, S. Chauhan, M. Rao, Design of a cnn based autonomous sitting posture recognition system, in: 2024 16th International Conference on Computer and Automation Engineering (ICCAE), 2024, pp. 437–441. doi:10.1109/ICCAE59995.2024.10569487.

[18] A. Çalışkan, Detecting human activity types from 3d posture data using deep learning models, Biomedical signal processing and control 81 (2023) 104479. doi:10.7717/peerj-cs.442.

[19] S. Abdullah, S. Ahmed, C. Choi, S. H. Cho, Distance and angle insensitive radar-based multi-human posture recognition using deep learning, Sensors 24 (2024). doi:10.3390/s24227250.

[20] P. Vermander, A. Mancisidor, I. Cabanes, N. Perez, Intelligent systems for sitting posture monitoring and anomaly detection: an overview, Journal of neuroengineering and rehabilitation 21 (2024) 28. doi:10.1186/s12984-024-01322-z.

[21] D. F. Odesola, J. Kulon, S. Verghese, A. Partlow, C. Gibson, Smart sensing chairs for sitting posture detection, classification, and monitoring: A comprehensive review, Sensors 24 (2024) 2940. doi:10.3390/s24092940.

[22] R. Saddaoui, M. Gana, H. Hamiche, M. Laghrouche, Wireless tag sensor network for apnea detection and posture recognition using lstm, IEEE Embedded Systems Letters 16 (2024) 469–472. doi:10.1109/LES.2024.3410024.

[23] M. F. Rybski, L. Juckett, Posture, in: Kinesiology for Occupational Therapy, Routledge, 2024, pp. 261–289.

[24] W. Zhang, W. Tan, S. G. Zammar, K. Park, J. Scheer, Y. Lee, A. Jamison, L. A. Tan, Cervical spine deformity, Adult and Pediatric Spinal Deformities-Recent Advances and Evolution of Technologies: Recent Advances and Evolution of Technologies (2024) 59.

[25] O. Kovalchuk, V. Slobodzian, O. Sobko, M. Molchanova, O. Mazurets, O. Barmak, I. Krak, N. Savina, Visual analytics-based method for sentiment analysis of covid-19 ukrainian tweets, in: International Scientific Conference "Intellectual Systems of Decision Making and Problem of Computational Intelligence", Springer, 2022, pp. 591–607. doi:10.1007/978-3-031-16203-9_33.

[26] Melsmm, Posture keypoints detection, 2022. URL: https://www.kaggle.com/datasets/melsmm/posture-keypoints-detection.

[27] O. Sobko, O. Mazurets, M. Molchanova, I. Krak, O. Barmak, Method for analysis and formation of representative text datasets, in: CEUR Workshop Proceedings, volume 3899, 2025, pp. 84–98. URL: https://ceur-ws.org/Vol-3899/paper9.pdf.

[28] Ultralytics, Yolo11s pose model, 2024. URL: https://huggingface.co/Ultralytics/YOLO11/blob/a01aaa06caeff788b052e193acb76b3f21571b3a/yolo11s-pose.pt.

[29] I. Krak, V. Didur, M. Molchanova, O. Mazurets, O. Sobko, O. Zalutska, O. Barmak, Method for political propaganda detection in internet content using recurrent neural network models ensemble, in: CEUR Workshop Proceedings, volume 3806, 2024, pp. 312–324. URL: https://ceur-ws. org/Vol-3806/S_36_Krak.pdf.

[30] I. Krak, O. Zalutska, M. Molchanova, O. Mazurets, R. Bahrii, O. Sobko, O. Barmak, Abusive speech detection method for ukrainian language used recurrent neural network, in: CEUR Workshop Proceedings, volume 3688, 2024, pp. 16–28. doi:10.31110/COLINS/2024-3/002.

[31] R. Zulunov, U. Akhundjanov, K. Musayev, B. Soliyev, A. Kayumov, M. Asraev, Building and predicting a neural network in python, E3S Web Conf. 508 (2024) 04005. doi:10.1051/e3sconf/202450804005.

[32] O. Rainio, J. Teuho, R. Klén, Evaluation metrics and statistical tests for machine learning, Sci. Rep. 14.1 (2024). doi:10.1038/s41598-024-56706-x.

[33] G. Naidu, T. Zuva, E. M. Sibanda, A Review of Evaluation Metrics in Machine Learning Algorithms, in: Artificial Intelligence Application in Networks and Systems, Springer International Publishing, Cham, 2023, pp. 15–25. doi:10.1007/978-3-031-35314-7_2.