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Assessing the Impact of Prolonged Sitting and Poor Posture on Lower Back Pain: A Photogrammetric and Machine Learning Approach

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Abstract: Prolonged static sitting at the workplace is considered one of the main risks for the development of musculoskeletal disorders (MSDs) and adverse health effects. Factors such as poor posture and extended sitting are perceived to be a reason for conditions such as lumbar discomfort and lower back pain (LBP), even though the scientific explanation of this relationship is still unclear and raises disputes in the scientific community. The current study focused on evaluating the relationship between LBP and prolonged sitting in poor posture using photogrammetric images, postural angle calculation, machine learning models, and questionnaire-based self-reports regarding the occurrence of LBP and similar symptoms among the participants. Machine learning models trained with this data are employed to recognize poor body postures. Two scenarios have been elaborated for modeling purposes: scenario 1, based on natural body posture tagged as correct and incorrect, and scenario 2, based on incorrect body postures, corrected additionally by the rehabilitator. The achieved accuracies of respectively 75.3% and 85% for both scenarios reveal the potential for future research in enhancing awareness and actively managing posture-related issues that elevate the likelihood of developing lower back pain symptoms.

Keywords: photogrammetry; MSDs; low back pain; ergonomics; incorrect sitting posture; postural angles; body markers; self-assessment; ML models; classification

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1. Introduction

The seated position is prevalent in the workplace and can exert significant strain on the musculoskeletal system. As an increasing number of occupations involve prolonged static sitting, contributing to a sedentary lifestyle, the prevalence of adverse health effects is on the rise. Ergonomics plays a crucial role in establishing a favorable relationship between individuals and their work, thereby contributing to enhanced worker health [1].

Extended periods of static sitting are associated with the development of musculoskeletal disorders (MSDs), a prevalent issue in Europe [2]. MSDs exert a negative impact on the musculoskeletal system and can lead to severe health problems, particularly when compounded by negative emotions, stress, and heightened cognitive demands. The modern workplace, characterized by widespread use of electronic devices, amplifies the risk of MSDs, especially among students, with up to 65% experiencing such disorders. Contributing factors include a lack of rest (85%), passive load (70%), poor body posture (60%), and overwork (30%) [3,4].

A large-scale survey [5] designed to assess the determinants of posture in a large metropolitan area population found that 68.7% of respondents felt that not enough attention is paid to posture in the workplace. Our previous study [6] among 200 prolonged sitting workers showed that 67% of people well-informed about correct working posture suffered from pain in the head, neck, upper or lower back, and waist.

Vertebral segments of the human spine are known to function synergistically to maintain the stability of the human body. Altered vertebral motion has been widely assumed as a biomechanical factor causing spinal pathology [7]. An estimated 7% of all visits to a primary care physician are due exclusively to low-back pain (LBP) [8]. LBP is also the most common musculoskeletal complaint that physiotherapists deal with [9]. Most people (60–70%) experience at least one episode of LBP at some point in their life [10].

Lumbar disc degeneration is among the most common reasons for the development of lower back pain [11]. Causes of physical imbalances, disc degeneration, and lower back pain are complex and multifactorial, caused by processes including aging, abnormal mechanical loads, incorrect sitting, incorrect working posture, and accidental damage. Degenerative disease of the lumbar spine is not only the cause of pain in numerous patients but has also become an excessive social burden in various countries [12]. Therefore, understanding the underlying mechanisms causing pain due to the degeneration of lumbar discs is important when analyzing the basic principles of spine biomechanics and maintaining a correct sitting posture to ensure a healthy spine and pelvis [13].

Evaluating spinal posture is crucial in understanding and addressing low back pain, as abnormal postural behavior is identified as a potential risk factor for lumbar injury. Extended periods of poor posture, such as slouching or maintaining a bent position, impose biomechanical stress on the lower back, affecting spinal alignment and causing strain on supporting structures [14]. Therefore, it is crucial to examine how prolonged sitting affects an individual's health, specifically whether it leads to lumbar discomfort or lower back pain.

Numerous studies have explored various postures to identify optimal sitting positions. While a consensus on the optimal sitting posture remains elusive, an upright lordotic posture is generally regarded as conducive to spinal health [15].

Ensuring a conducive ergonomic work environment, adopting proper sitting habits, and incorporating regular breaks, along with adequate lumbar support and posture awareness, are crucial in minimizing the risk of musculoskeletal issues and fostering spinal health.

A recommended 90-degree knee angle contributes to lumbar support by minimizing lower back strain and fostering a neutral and comfortable sitting posture. This position offers advantages such as decreased pressure on the knee joints, promoting even weight distribution, and averting discomfort associated with extended sitting. Additionally, it facilitates improved blood circulation, reducing the likelihood of leg numbness or tingling.

Numerous studies examining correct sitting postures have employed various methodologies in recent years. The questionnaire approach for assessing good body posture and related musculoskeletal disorders (MSDs) involves the use of structured surveys to gather subjective information from individuals regarding their sitting or standing habits, ergonomic practices, and experiences of discomfort or pain [16–18]. These questionnaires typically inquire about the frequency and duration of prolonged sitting or standing, the use of ergonomic furniture, and the presence of any musculoskeletal symptoms. By utilizing this approach, researchers aim to gain insights into participants' perceptions of their posture and the potential association with MSDs, providing valuable qualitative data for further analysis and understanding.

Recently, there has been a growing trend in utilizing sensor-based recognition systems that collect data through accelerometers, pressure sensors, or ultrasonic sensors. For instance, Tsai et al. [19] proposed an automated pressure sensor-based sitting posture recognition system designed to facilitate users in reviewing historical data and addressing potential health risks associated with poor posture. However, the implementation of pressure sensors mounted on a chair complicates the experimental setup.

Alternatively, some researchers have explored using postural angles as measurable variables to evaluate posture correctness [20,21]. These angles are assessed through methods such as goniometry, photography, photogrammetry, and radiography, with photogrammetry standing out as a widely adopted noninvasive approach that eliminates the risk of radiation exposure associated with radiography.

A comprehensive review of machine learning (ML) algorithms focused on musculoskeletal disorders (MSD) prevention was presented in [22], outlining some of the most frequently used techniques: Artificial Neural Networks (ANN), Decision Tree, Random Forest, and Support Vector Machines (SVM). Notably, about one fourth of the research papers were published in 2020.

A recent study proposed a sitting posture monitoring system using electromyographic (EMG) sensors and ML algorithms [23]. Support Vector Machine (SVM), K-nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), and Multi-Layer Perceptron (MLP) were used for detection of improper posture. A binary classification was performed (distinguishing between proper and improper posture) and multi-class classification (including some frequent deviations from the correct posture). The results outlined KNN as the best performing algorithm with accuracy reaching 91%. In another study [24], the authors utilized a hybrid sensor system and K-nearest Neighbors (KNN) model for recognition of correct posture with accuracy of up to 92%. Another research paper [19] presented successfully captured and recognized ten common sitting postures. The ML methods employed included SVM, KNN, DT, RF, and logistic regression (LR).

In this study, we explored the relationship between poor sitting posture during prolonged computer use and the occurrence of low back pain (LBP). The primary objective was to develop resources for further research and model creation to identify poor posture. We focused on the contributing factors of poor posture and extended sitting periods, utilizing a dataset to develop models for recognizing poor body posture. Our target population was young individuals in sedentary occupations, aiming to assess early-stage risks for the development of musculoskeletal disorders (MSDs). This experiment was conducted as part of the project "Ergonomic Research on Work-Related Health Problems by Innovative Computer Models with a Focus on the Prevention of Musculoskeletal Disorders".

2. Materials and Methods

The current research focuses on creating models for correct/incorrect body posture recognition based on postural angles in the lumbar region. Under the term incorrect posture is meant a position that increases the stress applied to the muscles and joints and increases the risk of discomfort or lower back pain. Figure 1 shows the structure of the experimental workflow.

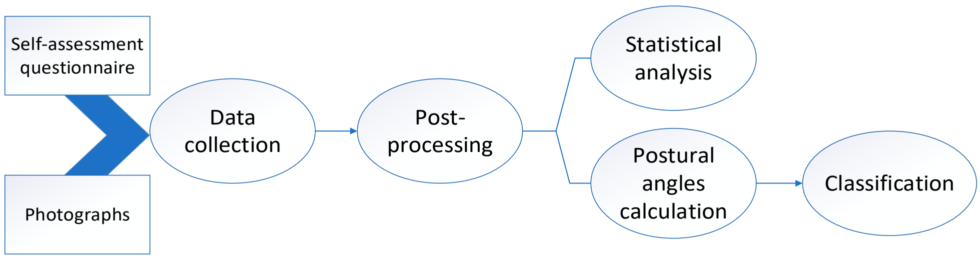

Figure 1. Structure of the experimental workflow.

The method used, consisting of calculation of postural angles (known as photogrammetry), considers the angles and distances relevant to posture correctness and is very straightforward with regard to the its usage in human anatomy assessment and particularly in ergonomics. In contrast with other methods like Convolutional Neural Networks (CNNs) which otherwise are very powerful in image classification, the photogrammetric approach does not require large datasets and usually returns reliable, consistent, and interpretable results without the need for extensive training which in the context of seated posture assessment are targeted for domain-specific implementation.

2.1. Experimental Procedure

The experimental procedure comprised several sequential steps:

(1) Volunteers filled out a self-assessment questionnaire regarding their work habits, ergonomic practices, and instances of discomfort or pain.
(2) Left lateral view photographs of the body were captured while volunteers were seated in their natural position in front of a computer, occupied with a game-like standard cognitive task.
(3) A physiotherapist corrected the seating body position and additional left lateral view photographs of the body were captured.
(4) The images of each of the 100 participants were post-processed and annotated by a physiotherapist with over 15 years of professional experience.
(5) Based on the placed markers, postural angles related to LBP were calculated.
(6) Statistical analysis of the self-assessment questionnaire responses was performed.
(7) The angle values, along with tags for incorrect were collected in a LBPA dataset and used for machine learning purposes, aiming to construct a model for recognizing improper sitting postures related to the occurrence of low back pain risk.

The data collection commenced following the acquisition of informed consent. Participants were summoned at the designated time. In essence, the data collection session was initiated with a procedural explanation, completion of the questionnaire, and capturing photographs of the subject in relaxed postures. The measurement of sagittal spine posture during computer task was conducted through digital photogrammetry.

The self-assessment questionnaire utilized in this study was specifically developed as outlined in [6]. It aimed to assess the levels of discomfort and pain arising from extended periods of computer work characterized by infrequent changes in body posture and suboptimal ergonomic organization of the workplace.

During the experiment, each participant was asked to sit on a standard office chair (42 cm in height) next to a non-adjustable office desk while using a desktop computer with standard peripherals. The participants were instructed to adopt their usual comfortable seated position while gazing at the computer monitor. Left lateral view photographs were captured to assess the sagittal alignment of the spine. A digital camera (Panasonic Lumix G80) mounted on a tripod, positioned 2.5 m away from the participant, was used for these photographs. A second photograph was taken after the participant's posture had been corrected by a physiotherapist with over 15 years of professional experience.

To calculate the desired postural angles, circular markers were carefully placed by the physiotherapist on specific vertebrae (T12, L5, and S1), as well as on the hip joint, knee joint, and ankle joint, as illustrated in Figure 1. This approach is a non-invasive, practical and valid research method, which simplifies decision making [25,26]. Although the proposed method does not replace medical radiological examinations, it can be repeated without limitations and is useful for developing continuous monitoring systems to prevent and detect potential spine problems. Additionally, Figure 2 shows photographs of a participant assuming his natural posture before (labeled as 'a') and after (labeled as 'b') corrections were made.

A dedicated software application, developed specifically for this study, was utilized to identify circular markers, and calculate the coordinates of their centers as numerical points in the image (Figure 2). These centers (points) served as the basis for con-structing necessary straight lines to measure angles between intersecting lines, including those connecting the points. According to the applied methodology, angles 2, 6 and 7 (Figure 3) were calculated, having a direct relationship with determining the sagittal imbalance and low back pain.

- Angle 2—Lumbar lordosis (LL), defined as the angle between tangential lines to the lower plateau of L5 and the top of L1.
- Angle 6—Hip joint angle measurement—sitting position. This is an angle obtained by the intersection of two lines in the region of the greater trochanter of the femur. One line is vertical and parallel to the trunk, and the other line is parallel to the long

axis of the femur in line with the lateral femoral condyle. The angular measurement method employed in this study was adapted from our previous research

- Angle 7—Bent knee angle when sitting. This is an angle obtained by the intersection of two lines in the region of the lateral epicondyle of the femur. One line is horizontal and parallel to the femur to the greater trochanter, and the other line is parallel to the fibula to the lateral malleolus.

(**a**) (**b**)

Figure 2. Participant's posture with body markers: natural sitting posture (**a**) and corrected sitting posture (**b**).

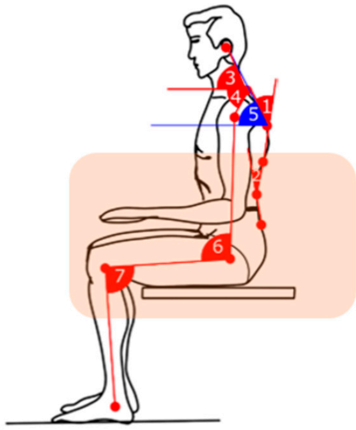

Figure 3. Postural angles (1–7) with focus on those related to higher risk of low back pain development.

2.2. Participants

The study encompassed a total of 100 volunteers, with a gender distribution of 64% males (n = 64) and 36% females (n = 36). The mean age of the participants was 28.38 (±11.19), height 174.31 (±10.20), and weight 75.27 (±17.50). The survey was conducted in Bulgaria during the months of November and December 2021.

It was ensured that the participants had no structural spinal curvature, neurological disease, chronic inflammatory disease, joint-related conditions, or ongoing pregnancies. The participants were informed of the procedure and signed an informed consent declaration before their involvement.

2.3. Dataset

The data was collected from one hundred participants. The LBPA (Low Back Pain Assessment) dataset consists of left-side view pictures with markers (natural sitting posture and corrected sitting posture), a file with postural angle calculations and tags, a file based on the questionnaire, representing the self-assessment of the respondents. The description of the data is as follows:

- Pictures with markers—Pictures in .jpg with markers ready to use (ten markers corresponding to body map). File name format is "ID.X", where ID corresponds to Participant ID numbers and "X" denotes the natural sitting posture (5) and the corrected posture (6). Photo IDs correspond to Questionnaire IDs;
- Postural angle calculations—Angle.csv file containing in each column postural angle calculations (angle 2, angle 6, angle 7)
- a file with questionnaire responses

Additional information about our research and the presented dataset can be found on Supplementary Materials.

The LBPA database is a supplementary component of a larger research presented in [27].

2.4. Data Processing and Statistics

To investigate the potential relationship between low back pain and incorrect body posture, which leads to increased load on the lumbar region, we analyzed self-reported questionnaire results from each participant regarding their work habits, ergonomic practices, and instances of discomfort or pain attributed to prolonged computer use.

Following the methodology described in Section 2.1, a set of features was calculated and used to develop models for recognizing good/correct and poor/incorrect sitting postures that increase the lumbar load of the body in two scenarios. In both scenarios, binary detectors were trained in a person-independent setup using tags defined by the physiotherapist.

The first scenario utilized data extracted from the photographs of volunteers seated naturally (100 cases total), with tags indicating good and poor postures. The second scenario involved data from two photographs of each volunteer identified as sitting incorrectly—before and after postural correction from the medical specialist (120 cases total)—to achieve a balanced dataset.

We developed distinct detectors for each scenario through experiments involving established classification algorithms, including Decision Tree (DT), Naive Bayes (NB), Logistic Regression (LR), Generalized Linear Model (GLM), Fast Large Margin (FLM), Random Forest (RF), Gradient Boosted Trees (GBT) and Deep learning (DLNN). The diversity of chosen methods allowed benchmarking, considering the nuances in the data and especially the relationship between postural angles and respectively correct or incorrect posture. These nuances provoked the usage of different approaches toward the binary classification problem with regard to complexity, ranging from simplest (Naive Bayes and Logistic Regression) to highly complex methods (Gradient Boosted Trees and Deep Learning); handling nonlinearities by inclusion of models (Decision Trees, Random Forests, Deep Learning, etc.) adept in processing such data; robustness to overfitting by inclusion of ensemble methods as well as balance in the trade-off between performance (focus on maximizing predictive power) and interpretability (with regard to how each feature affects the prediction).

The classification experiments were carried out using RapidMiner Studio (© 2024 RapidMiner, Inc. (Troy, MI, USA). All Rights Reserved. Documentation available at https://docs.rapidminer.com/latest/studio/index.html, 5 April 2024) (version 10.2)), employing the 10-fold cross-validation methodology with automated optimization of classifier parameters, ensuring consistency across all experiments. In addition, fine tuning of hyper parameters was conducted to the best performing classifiers.

The performance of the binary classification tasks was evaluated using metrics like accuracy, calculated as the percentage of correct predictions over the total number of predictions; recall—as the proportion of all actual positives that were classified correctly as positives (true positives plus false negatives); precision—as proportion of all the positive classifications that are actually positive and F-measure—as harmonic mean of precision and recall.

3. Results

3.1. Questionnaire-Based Analysis

The questionnaire approach for assessing good body posture and related musculoskeletal disorders (MSDs) involves the statistical analysis of data collected from participants regarding their sitting habits, ergonomic practices, and experiences of discomfort or pain. This analysis aims to quantify and interpret the participants' perceptions of their posture and the potential associations with MSDs.

The findings revealed that 37.5% of participants utilized a computer for over 4 h daily for 6 to 12 years. Additionally, 54% reported experiencing discomfort or pain in the lower back during prolonged computer use, with 20% specifying such occurrences at least once daily. The degree of pain assessed by the participants is presented in Table 1. More than half of the responders (53%) reported a severe degree of pain or discomfort, while 46% reported experiencing a moderate level of discomfort, with 5% indicating a high intensity of pain in the back.

Table 1. Self-Reported Discomfort or Pain Among Participants Resulting from Prolonged Computer Work.

Degree of Pain/Discomfort	Mild Pain	Moderate Pain	Severe Pain	Very Severe	Worst Pain Possible
Back pain	12	18	20	4	2
Low back pain	9	16	21	7	1
Pain in the buttock	10	11	12	2	2
Total people with pain or discomfort (%)	31%	45%	53%	13%	5%

3.2. Photogrametric Analysis

To assess the pelvic position and spinal load during the seated body's working position, a photogrammetric analysis was conducted on photographs of 100 individuals. This approach involved calculating specific angles, namely angle 2, angle 6, and angle 7, providing insights into the biomechanics of the seated posture.

The box plot depicted in Figure 4 presents the statistical distribution of data about postural angles 2, 6, and 7 for all participants. Notably, the recommended angle of 90 degrees in the knee joint (7) during seated work is observed in less than 25% of individuals. This indicates that many participants place undue stress on their knee joints, leading to uneven weight distribution. Furthermore, this improper posture hinders blood circulation and elevates the risk of numbness in the extremities. It is imperative to note that incorrect sitting posture is correlated with increased discomfort and pain.

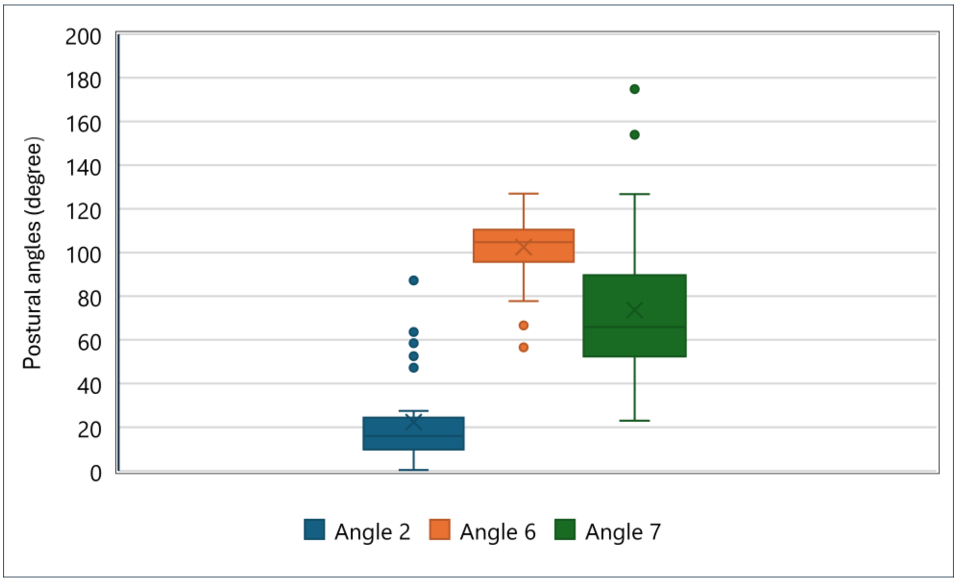

Figure 4. Box plot representation of distributions of the postural angles (2, 6, 7) for 100 participants.

3.3. Detection of Poor Body Posture

3.3.1. Natural Postures-Based Scenario

In the current study, we investigated the possibility of automated detection of good versus poor body posture utilizing postural angles (specifically, angle 2, 6, 7) derived from photographs of the participants in natural body postures. “Natural sitting body posture” refers to the posture that feels most comfortable and intuitive to an individual, which may not necessarily align with ergonomic guidelines. The set of features is freely available in the LBPA dataset. The tags noted by a medical doctor correspond to incorrect posture in the lumbar region, which increases the risk of lumbar pain, even if this pain is not yet chronic or reported.

Table 2 displays the experimental results, obtained by the set of classifiers (ref. Section 2.4) with their metrics—accuracy, recall, precision and F1 score, known also as F-measure with their standard deviations. Across all investigated cases, the Naïve Bayes classifier performed with the highest accuracy of 75.3% which could be classified as moderate along with its precision of 73.3% and very high recall of 95.0%. It generally shows strong performance in identifying incorrect pose but struggles with the accuracy, probably due to the high variance, reflected in standard deviation of 11.2%. GLM despite the high recall shows inability to correctly classify the proper postures which strongly reduces its utility. LR and FLM show identical metrics which could be assessed as balanced but low effective compared to others. DLNN show moderate performance, but its high standard deviation in accuracy speaks for potential instability in the model effectiveness. DT exhibits perfect recall but low accuracy and precision which could be due to a potential overfitting issue. Both methods RF and GBT show a similar moderate performance across metrics, however RF shows higher stability comparing their standard deviations in accuracy. SVM is one of the better performers in this scenario showing higher metrics than the most of the models, but still struggling with its stability (high standard deviation).

Table 2. Correct sitting posture detection in natural postures-based scenario.

Classifier Type	Accuracy [%], st.dev. [%]	Recall [%], st.dev. [%]	Precision [%], st.dev. [%]	F-Measure [%], st.dev. [%]
Naïve Bayes	75.3% ± 11.2%	95.0% ± 11.2%	73.3% ± 19.0%	80.7% ± 9.0%
Generalized Linear Model	57.3% ± 18.2%	95.0% ± 11.2%	55.3% ± 18.3%	68.2% ± 14.6%
Logistic Regression	60.7% ± 13.6%	90.0% ± 13.7%	60.7% ± 13.6%	71.5% ± 10.8%
Fast Large Margin	60.7% ± 13.6%	90.0% ± 13.7%	60.7% ± 13.6%	71.5% ± 10.8%
Deep Learning	63.3% ± 22.9%	95.0% ± 11.2%	63.3% ± 22.9%	74.1% ± 16.6%
Decision Tree	59.3% ± 18.9%	100.0% ± 0.0%	59.3% ± 18.9%	73.0% ± 15.2%
Random Forest	61.3% ± 16.8%	95.0% ± 11.2%	61.0% ± 20.1%	72.0% ± 14.8%
Gradient Boosted Trees	59.3% ± 25.2%	95.0% ± 11.2%	61.3% ± 24.7%	72.2% ± 18.2%
SVM	64.7% ± 19.5%	100.0% ± 0.0%	62.0% ± 21.0%	74.8% ± 18.6%

Since the difference in the accuracy between the first (NB) and the second (SVM) ranked clarifiers was too large (above 10%), additional fine tuning with Laplacian correction was performed only to the Naïve Bayes classifier, which did not change its accuracy. The observed lower detection accuracy can be attributed to the demographic and sports activity profile of the volunteers. Many of the participants were young individuals who actively engaged in sports, with 40% maintaining sitting positions that do not place significant stress on the lumbar region, thereby reducing the incidence of low back pain. In the context of unbalanced datasets, standard performance measures such as accuracy can be misleading. When the majority class dominates, the model may predict the majority class more frequently, leading to an inflated accuracy metric that does not reflect the model’s performance on the minority class. This bias towards the majority class results in poor detection of the minority class, which in this case, is the group exhibiting correct sitting body posture with good lumbar support for the lower back.

Addressing these issues requires resampling techniques to improve the model's sensitivity to the minority class and the classification accuracy. The overall performance of the detection models in Section 3.3.2 was significantly improved by utilizing the balanced dataset.

3.3.2. Corrected Postures-Based Scenario

In the second scenario, the two-class classification is based on feature vectors computed from photographs of only a portion of the participants (60%) marked by the physiotherapist as sitting in poor work postures. The two classes are composed of the postural angles derived from the photos of an incorrect body posture and photos of the same participants after their sitting body position has been corrected by the expert. Following the procedure outlined in Section 2.4 we used nine classification methods and ten-fold cross validation to create automated models for the detection of sitting posture with good lumbar support for the lower back.

Comparison of the performance of all classifiers with automatic optimization in the corrected postures-based scenario is presented in Table 3.

Table 3. Correct sitting posture detection in corrected postures-based scenario.

Classifier Type	Accuracy [%], st.dev. [%]	Recall [%], st.dev. [%]	Precision [%], st.dev. [%]	F-Measure [%], st.dev. [%]
Naïve Bayes	73.3% ± 7.2%	46.7% ± 13.9%	100.0% ± 0.0%	62.7% ± 12.8%
Generalized Linear Model	76.7% ± 7.2%	71.7% ± 18.3%	84.3% ± 15.1%	75.4% ± 9.4%
Logistic Regression	76.7% ± 7.2%	71.7% ± 18.3%	84.3% ± 15.1%	75.4% ± 9.4%
Fast Large Margin	74.3% ± 6.4%	73.3% ± 18.1%	78.3% ± 12.6%	73.8% ± 7.9%
Deep Learning	79.5% ± 7.5%	71.7% ± 29.8%	83.3% ± 15.6%	71.5% ± 13.9%
Decision Tree	72.9% ± 14.6%	93.3% ± 14.9%	66.3% ± 11.9%	77.3% ± 12.5%
Random Forest	80.0% ± 16.3%	93.3% ± 14.9%	79.0% ± 14.3%	83.7% ± 6.1%
Gradient Boosted Trees	78.6% ± 18.9%	73.3% ± 36.5%	81.0% ± 20.7%	72.9% ± 26.3%
SVM	73.3% ± 12.4%	61.7% ± 28.6%	79.3% ± 21.7%	66.3% ± 21.5%

In this scenario the RF classifier outperformed the rest of the algorithms with achieved accuracy of 80%, recall of 93.3% and precision of 79.0%, demonstrating strong and stable performance. Notably, the second (DLNN) and the third (GBT) ranked classifiers achieved accuracies very close to the first one, respectively 79.5% and 78.6% accompanied by strong recall and precision. Although their performance metrics were similar to RF they both showed high standard deviations suggesting instability of the underlying models. The rest of the models showed lower effectiveness metrics and higher variances and thus seemed less suited to compare with the winners. The optimal parameters of the first three classifiers set automatically were as follows: Random Forrest—number of trees: 100; maximal depth: 2; Deep Neural Network—four-layer feed forward architecture 3/50/50/2 as the first three layers consist of neurons with ReLU activation function and the last layer consists of two neurons with SoftMax activation function; Gradient Boosted Trees: number of trees 100; maximal depth: 2; learning rate: 0.001.

These three algorithms were additionally finetuned for improvement of their accuracies. The results and the respective optimal parameters are shown in Table 4.

Table 4. Correct sitting posture detection in corrected postures-based scenario after finetuning of the hyperparameters of the first three ranked classifiers.

Classifier Type	Optimal Parameters	Accuracy [%]	Recall [%]	Precision [%]	F-Measure [%]
Random Forest	number of trees 100; criterion Gain Ratio; max depth 10; voting strategy: majority vote	85.00% ± 12.30%	85.0% ± 21.44%	86.79% ± 12.88%	85.89% ± 12.63%
Deep Learning	3/100/100/2 architecture; the first three layers—neurons with Maxout activation functions, and the two output neurons have SoftMax activation functions.	82.50% ± 12.08%	91.67% ± 11.79%	80.19% ± 15.40%	85.55% ± 10.16%
Gradient Boosted Trees	number of trees: 50; max depth: 3; learning rate: 0.01	81.67% ± 16.57%	80.00% ± 17.21%	83.95% ± 18.02%	81.93% ± 12.45%

The results achieved after the finetuning of hyperparameters were considerably improved, both regarding the performance parameters and the standard deviations, demonstrating well-calibrated models. The best performance reaching accuracy of 85.00% (resp. standard deviation of ± 12.30%) was achieved by the RF classifier. Figure 5 depicts the accuracies of all ML methods achieved in both scenarios before and after fine-tuning of the hyperparameters.

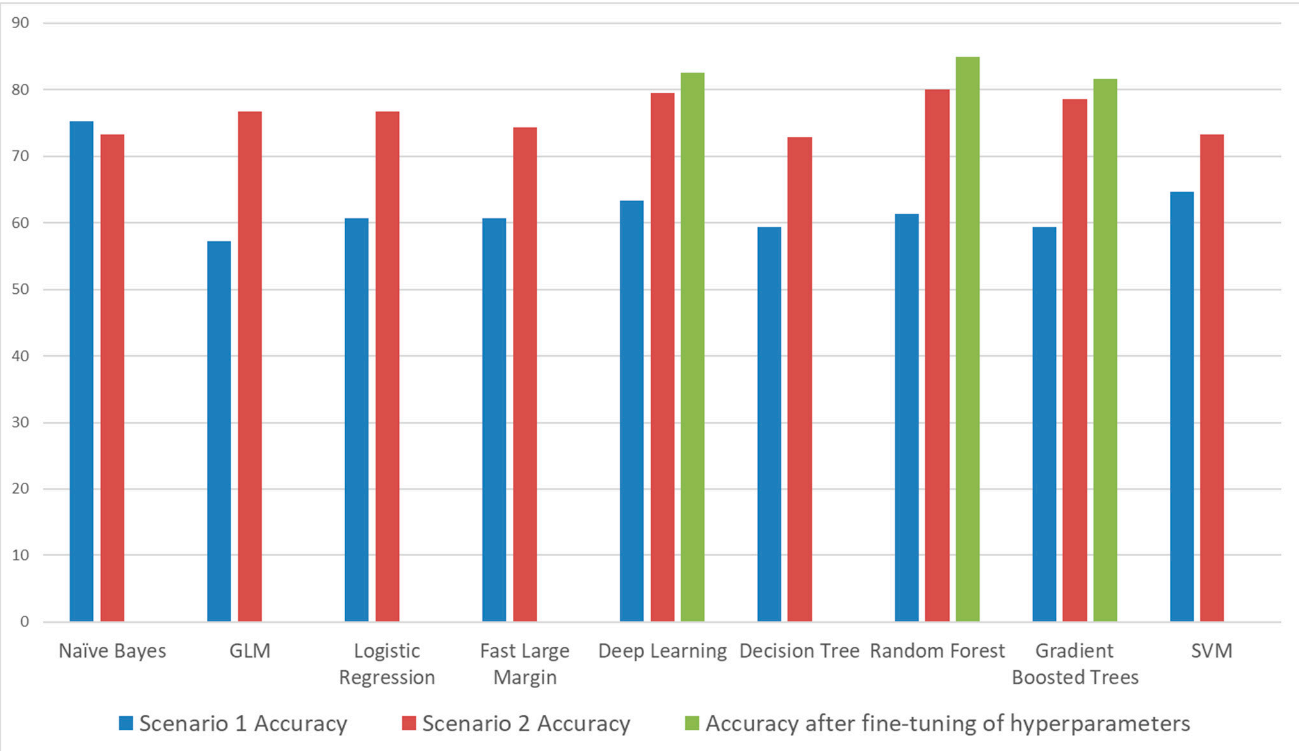

Figure 5. Accuracies of all ML methods achieved in both scenarios before and after fine-tuning of the hyperparameters.

Figure 6 shows assessment of the importance of each of the three angles with regard to prediction of correct/incorrect posture with the RF classifier implemented with SHAP (SHapley Additive exPlanations, v0.45.1) in Python 3.

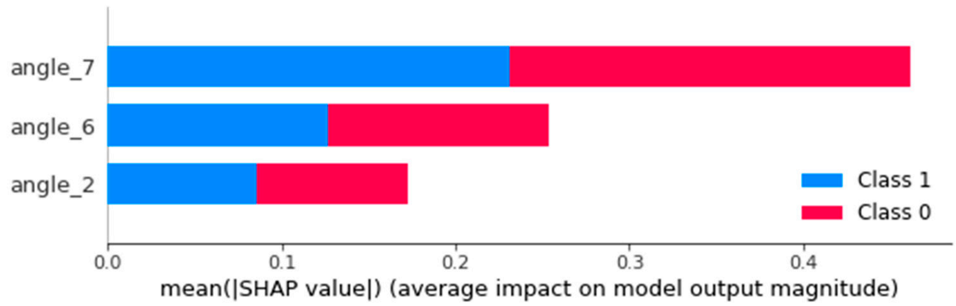

Figure 6. Assessment of feature importance for prediction of incorrect posture with Random Forest classifier.

The results from this SHAP analysis suggest that angle_7 is the most decisive factor in predicting correct/incorrect posture followed by angle_6 which is also a significant factor for that. Angle_2 is less impactful but still contributes to refining the model's predictions. This insight can be useful for focusing the attention on building habits for maintaining the right angle-value of angle_7 (around 90 degrees) for avoiding the risk of LBP effectively.

4. Discussion

The causal relationship between poor sitting habits and LBP is still controversial and probably it will take additional time and effort for a consensus on that topic to be established. Two polar positions could be outlined regarding the understanding of such causality. On the first side are supporters of the strong correlation between the sedentary lifestyle and the risk of LBP. Several recent studies [28–30] confirm this relationship. On the opposite side are studies that either reject the link between the (working) posture and LBP [31] or at least cannot find satisfying scientific evidence about it [32–34], underscoring the influence of other personal characteristics, such as age, gender, height, weight, etc. The supporters of the first point of view weigh out the influence of different factors, such as prolonged sitting or improper posture as more harmful to people's health. Contrary to this, [31] even argues that there is no such thing as incorrect posture.

While we do not directly take side in this discussion and consider the arguments of each of the mentioned research studies, we do believe that people exposed to both prolonged sitting and improper posture are at risk of the development of MSDs and LBP, without underestimating the rest of the factors.

The aim of the collected LBPA dataset was to contribute to the research devoted to the occurrence of LBP in a way that can prevent young people from developing MSDs on an elder age. This was also the main reason to employ students with computer science profiles for volunteers as they were exposed to prolonged static sedentary work, often accompanied with poor body posture. In our study, it was found that 37.5% of the participants had been using a computer for more than 4 h per day for the last 6 to 12 years.

Additionally, 54% reported experiencing lower back discomfort or pain during prolonged computer work, with 20% repeating such occurrences at least once a day. The data shows similarity to a study [35], which reported that low back pain had a prevalence of 59.5% among their study participants (n = 120). Another study [36] reported that men and women working with computers in the office had respectively 42% and 45% prevalence of low back pain. The results from the conducted self-assessment survey proved the relevance of the research, even though the average age of the participants was quite young (28.38 years) and not expected to show occurrence of MSDs. In that context, we consider the efforts for data collection and modeling as important regarding the opportunities for prevention of LBP and similar symptoms.

Models for detection of poor posture leading to increased load on the lumbar region, developed in two scenarios, show the potential for technological support of the ergonomic organization of the workplace in occupations associated with prolonged sedentary working posture. Scenario 1 uses machine learning algorithms trained with features set derived from photographs of the participants in natural body postures. In scenario 2, models are trained with data extracted from photographs of the participants with poor sitting body positions and photos of the same participants after the correction of their postures by the expert. We recognize that these postures are snapshots that cannot lead to general conclusions about the development of LBP. Still—they show to a big extent the working habits of each participant (especially when their attention is focused on a cognition demanding task, as was the case with the experimental setup of the current study). Another limitation of the proposed methodology is the possibility of error in the process of placing the markers and calculating the postural angles, for which reason we relied to an experienced professional in the field of physiotherapy and medicine.

We consider that the LBP dataset could be an useful resource during the development of tools for real-time detection of poor sitting postures. The provided analysis and the proposed models could be used for development of effective, non-intrusive, low-cost solutions for diminishing the risk of LBP-connected issues in the contemporary ergonomic design of the working spaces.

Supplementary Materials: The following supporting information can be downloaded at: https://www.wwwsensornetworkslab.com/projects/ergo-research, The LBPA dataset, accessed on 11 September 2024.

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Data Availability Statement: The LBPA dataset supporting reported results can be downloaded from the website link: https://www.wwwsensornetworkslab.com/projects/ergo-research, accessed on 11 September 2024.

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