JOURNAL OF MODERN SCIENCE
SPECIAL ISSUE
3/57/2024
www.jomswsge.com
DOI: doi.org/10.13166/jms/191431

BEATA WÓJCIK
WSEI University in Lublin, Poland
0000-0003-4083-8468

MICHAŁ BŁASZCZYKOWSKI
Lublin University of Technology, Poland
ORCID iD: orcid.org/0009-0007-4025-6843

EDMUND WĄSIK
WSEI University in Lublin, Poland
ORCID iD: orcid.org/0009-0002-3848-6117

HUMAN MOVEMENT MONITORING SYSTEM FOR CLASSIFICATION OF STRENGTH EXERCISES AND VERIFICATION OF THEIR EXECUTION TECHNIQUE

SYSTEM MONITOROWANIA RUCHU CZŁOWIEKA DO KLASYFIKACJI ĆWICZEŃ SIŁOWYCH ORAZ WERYFIKACJI ICH TECHNIKI WYKONANIA

Abstract

Human movement analysis is critical to optimizing sports training and influencing exercise intensity and effectiveness. In the age of modern technology, more and more advanced systems are emerging to support coaches and expand the range of analysis performed. This article aims to verify that artificial intelligence, together with machine learning algorithms, can accurately classify exercises in a dynamic gym environment and effectively assess the correctness of their performance. For the initial analysis of movement, the Google MediaPipe Pose model was used, which was responsible for detecting the human silhouette and determining the coordinates of the position of critical joints. Based on these coordinates, the angles between each joint were calculated, and then their sequences were further analyzed. The sequences were analyzed using the following three algorithms: support vector machine (SVM), dense neural network, and LSTM recurrent network. As a result, the system based on recurrent LSTM networks achieved the best prediction efficiency of approximately 98%, enabling accurate exercise classification. Subsequently, verification of the activities' correctness was also carried out, and the system, based on recursive LSTM networks, again achieved the best efficiency, this time equal to 96% on average for all exercises. On this basis, it was concluded that the discussed approach enables practical analysis of human movement, which can significantly improve training methods and facilitate coaching work.

Streszczenie

Analiza ruchu człowieka jest kluczowym aspektem optymalizacji treningów sportowych, wpływającym na intensywność oraz efektywność wykonywanych ćwiczeń. W dobie nowoczesnych technologii, pojawiają się coraz bardziej zaawansowane systemy wspierające trenerów, a także poszerzające gamę przeprowadzanych analiz. Niniejszy artykuł ma na celu zweryfikowanie, czy sztuczna inteligencja wraz z algorytmami uczenia maszynowego jest w stanie precyzyjnie klasyfikować ćwiczenia w dynamicznym środowisku siłowni, a także skutecznie oceniać poprawność ich wykonania. Do wstępnej analizy ruchu wykorzystany został model Google MediaPipe Pose, odpowiedzialny za wykrywanie sylwetki człowieka oraz wyznaczanie współrzędnych położenia kluczowych stawów. Na podstawie tych współrzędnych obliczone zostały kąty pomiędzy poszczególnymi stawami, a następnie ich sekwencje poddane zostały dalszej analizie. Wspomniane sekwencje, przeanalizowane zostały za pomocą trzech następujących algorytmów: maszyny wektorów nośnych (SVM), gęstej sieci neuronowej oraz sieci rekurencyjnej LSTM. W rezultacie, system opierający się na rekurencyjnych sieciach LSTM osiągnął najlepszą skuteczność predykcji równą w przybliżeniu 98%, umożliwiając precyzyjną klasyfikację ćwiczeń. Następnie, przeprowadzona została również weryfikacja poprawności wykonywanych aktywności, a system bazujący na sieciach rekurencyjnych LSTM, ponownie osiągnął najlepszą skuteczność, tym razem wynoszącą 96% średnio dla wszystkich ćwiczeń. Na tej podstawie stwierdzono, że omawiane podejście umożliwia efektywną analizę ruchu człowieka, co może znacząco usprawnić metody treningowe oraz ułatwić pracę trenerską

Keywords: *human movement analysis, gym exercise classification, MediaPipe Pose, biomechanics of exercise, LSTM*

Słowa kluczowe: *analiza ruchu człowieka, klasyfikacja ćwiczeń na siłowni, MediaPipe Pose, biomechanika ćwiczeń, LSTM*

Introduction

Human motion analysis is becoming increasingly important in sports training, where its use contributes to optimizing many aspects of exercise, directly improving its effectiveness. Advanced technologies for motion analysis enable the automation of training processes, which can significantly relieve coaches and participants of routine duties, allowing them to focus on more complex aspects of training. This automation also allows us to observe and analyze more details and potential trends in movements, which can be vital in identifying periodicities and specific behavioral patterns. As a result, trainers can draw more precise conclusions that can lead to new training methods.

Modern applications and models for human movement analysis, designed especially for gymnastics and yoga, are already available on the market and work with good efficiency, mainly due to the use of a static background that facilitates recognition and interpretation of movements (Zhou, H. Y., Hu, H. S., 2008). Accurate tracking of body position is crucial to the accuracy of execution of individual positions, which directly affects the efficiency and safety of training. In the context of introducing motion analysis technology into strength training, there are numerous challenges, such as the dynamic environment of the gym, which limits the effectiveness of these systems. The presence of other users and equipment placement often leads to partial coverage of exercisers' bodies, making it challenging to track movements (Rodgers, M. M., Pai, V. M., Conroy, R. S., 2015) accurately. The diversity of strength training requires artificial intelligence models to identify a wide range of movement patterns and their complex relationships. In addition, varying lighting in different parts of the gym poses additional challenges for vision systems, potentially negatively affecting the quality of recorded images and leading to errors in body position recognition (Sohn, W. J., Sipahi, R., Sanger, T. D., Sternad, D., 2019). Despite these obstacles, the development of motion analysis technologies in strength training opens up promising opportunities that can significantly increase their effectiveness and accessibility.

The article explores the effective use of advanced deep machine learning models to classify and assess the correctness of the performance of essential strength exercises such as the deadlift, barbell squat, overhead barbell press, and biceps barbell raise. Publicly available videos of trainers and less experienced individuals demonstrating these exercises were used as research material to see if algorithms could not only distinguish between these types of exercises but also accurately assess the quality of their performance (Butler, K., Davies, D., Cartwright, H., Isayev, O. Walsh, A., 2018). The purpose of the study is not only to confirm the applicability of such technological solutions in sports practice but also to determine the potential scope for further development and improvement of the training process with the help of technological support. It will be crucial to decide whether algorithms can provide coaches and gym users with precise information that can be used to increase training efficiency, improve safety, and optimize training results (Sohn, W. J., Sipahi, R., Sanger, T. D., Sternad, D., 2019). The results of this study may also help expand the range of exercises included in the analysis, allowing for a more comprehensive evaluation of the results obtained (van der Kruk, E., Reijne, M. M., 2018).

The article analyzes whether machine learning-based analysis methods can effectively evaluate angle sequences during exercise. Accurate monitoring of biomechanical data, such as joint angles, is crucial to assessing exercise techniques. If the efficacy of these analyses is confirmed, it could indicate the applicability of these methods to evaluate a broader range of exercises. Research should also focus on determining optimal confidence intervals that will improve the accuracy of the analyses and facilitate real-time monitoring of movements. Introducing these technologies could significantly improve the quality of strength training, enabling more effective technique management and rapid adjustment of training programs based on reliable data. The development of these techniques in strength training opens up new opportunities for research and practical applications in sports and rehabilitation while improving exercise safety by reducing the risk of injury (Butler et al., 2018; Hsu, C.-W., Lin, C.-J., 2002; Sohn et al., 2019).

Research Methodology

The initial phase of the study focused on detecting the human skeleton and accurately determining the coordinates of critical joints using the Google MediaPipe Pose model, which was trained on various data sets. The model is highly effective in identifying autonomous structures, which is crucial for the accuracy of further analysis, including classification and exercise validity assessment (Albrecht, T., Slabaugh, G., Alonso, E., Al-Arif, S., 2017). MediaPipe Pose is an advanced computer vision model that accurately estimates a person's body position by recognizing and tracking 33 critical joints. The model works effectively under various lighting and background conditions, essential in dynamic environments (Ge, M., Su, F., Zhao, Z., Su, D., 2020). In addition, the use of standardized coordinates allows easy scaling and adaptation to different sizes and human silhouettes, ensuring high detection accuracy regardless of the distance of objects from the camera (Niewiadomski, R., Kolykhalova, K., Piana, S., Alborno, P., Volpe, G., Camurri, A., 2019).

MediaPipe Pose generalized well when analyzing videos of people exercising at the gym, accurately verifying the position of joints during exercises. Thanks to its advanced recognition technology, the model efficiently handled different types of movements, even the more dynamic and complex ones.

Figure 1. *Action of MediaPipe Pose for deadlifters*

Based on the coordinates of the joint's positions, a function has been implemented to determine the angles between three selected joints. Each center joint acts as a focal point, while the other two joints define the arms of the angle. Considering the 3 points $a = [a_x, a_y]$, $b = [b_x, b_y]$ and c $= [c_x, c_y]$, we can calculate the angle at point b using the arctangent function for two variables as follows:

$$\theta_{ba} = \arctan\left(a_y - b_y, a_x - b_x\right)$$

$$\theta_{bc} = \arctan\left(c_y - b_y, c_x - b_x\right)$$

The result will be given in radians; hence, it should be converted to degrees and normalized:

$$angle = |\theta_{bc} - \theta_{ba}| * \frac{180}{\pi}$$

The value remains unchanged if the calculated angle is less than 180 degrees. On the other hand, if the calculated angle exceeds 180 degrees, we apply an adjustment, subtracting the angle value from 360 degrees to obtain a more representative angle between the vectors. This way, the angle is adjusted from 0 to 180 degrees, facilitating interpretation and analysis.

In addition, MediaPipe Pose has a feature that can predict the position of obstructed joints based on visible joints. This functionality is essential in the dynamic environment of a gym, where users's movements can obscure body parts. This allows the system to continuously and accurately monitor posture and body movements, crucial for sports and fitness applications, providing uninterrupted activity tracking. After consultations with fitness professionals, it was decided that only critical joints would be used for classification purposes and to assess the correctness of exercise performance. These are the left and right ankle, the left and right knee, the left and right hip, the left and right elbow, and the left and right shoulder. According to specialists, the position of the joints above is sufficient to classify the exercises we are analyzing accurately. In addition, the isolated angles of these joints will be able to fully provide us with information about the technique of performing exercises and indicate possible mistakes of those who train. The vision system will operate at 30 frames per second, meaning that 30 angle values per second will be recorded for each joint. This data will then be recorded into data frames, enabling further, more complex analysis. With this sampling rate, tracking the dynamics of joint position accurately changes over time will be possible, which is crucial for evaluating exercise techniques and conducting advanced research on training effectiveness.

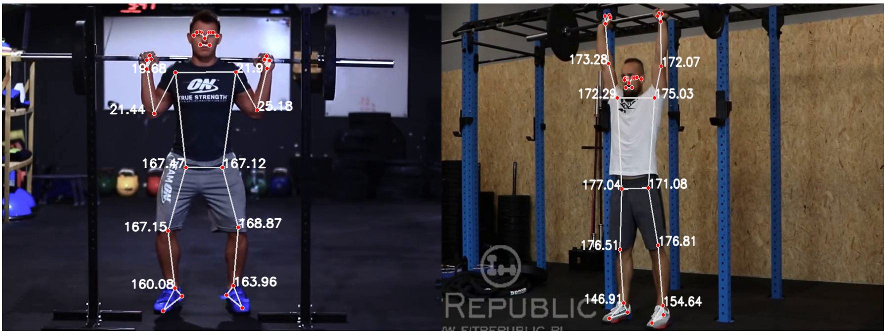
Figure 2. *Example of a data frame with stored angles*

	Left elbow	Right elbow	Left hip	Right hip	Left ankle	Right ankle	Left knee	Right knee	Left shoulder	Right shoulder
0	3.45	12.97	169.70	174.43	160.17	145.08	177.18	179.69	9.99	14.25
1	2.76	12.02	169.81	174.78	158.26	142.83	177.24	179.35	9.60	14.61
2	2.43	11.63	169.86	174.89	157.41	141.90	177.26	179.10	9.26	14.77
3	2.27	11.79	169.89	175.03	156.99	141.45	177.36	178.99	9.05	15.74
4	1.95	18.06	169.68	176.43	156.30	140.71	177.46	178.83	8.59	22.81
...	...	...	...	...	...	...	...	...	...	...
150	172.65	174.01	171.10	177.05	153.21	142.67	178.09	175.89	173.43	174.27
151	172.67	173.86	171.12	176.98	153.12	142.69	178.12	175.84	173.44	174.24
152	172.70	173.54	171.16	176.91	153.10	142.95	178.15	175.80	173.48	174.12
153	172.27	172.52	171.24	176.82	153.15	143.33	178.15	175.76	173.23	173.75
154	171.53	171.24	171.02	176.82	153.29	144.59	178.08	175.77	173.23	173.08

155 rows × 10 columns

Based on the analysis of the angles displayed in the videos of personal trainers, it is generally observed that symmetry is preserved on both sides of the body, indicating that the exercises are performed correctly. The observed fluctuations in the values of the angles are minimal, which further confirms the high precision and technical correctness of the movements performed. In the case of less-experienced individuals, much more significant discrepancies are observed between the angles on the left and right sides of the body. These differences in symmetry may indicate improper exercise technique or uneven muscle development. These discrepancies are essential because they can lead to improper loading of joints and muscles, which increases the risk of injury.

Figure 3: *Examples of correctly performed exercises with symmetry maintained*



The MediaPipe Pose model involves applying the results to side effects even in practical conditions. Different settings of the min_detection_confidence and min_tracking_confidence parameters were analyzed during the tests. The min_detection_confidence parameter, granted based on confidence, to consider the joint detection as successful, while min_tracking_confidence specifies some security that must be transmitted for the system to constitute already identified legal data (Patrona, F., Chatzitofis, A., Zarpalas, D., Daras, P., 2018). Tuning these parameters is crucial to assessing and improving exercise accuracy, which directly impacts the application of exercise technique analysis. We set the values for these parameters at 0.6, which is the difference between available devices and which omissions are valid under certain conditions. Thanks to this balance, the system functioned even in intelligent environments and low lighting, minimizing the risk of health errors (Rodgers, M. M., Pai, V. M., Conroy, R. S., 2015).

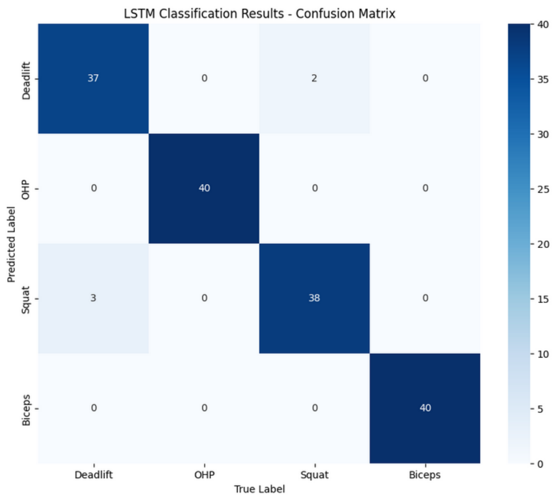
Classification of exercises

A dataset containing 203 videos illustrating biceps barbell bending, 200 videos depicting soldier presses, 201 videos of barbell squats, and 200 videos of deadlifts was used for the classification task. The average video length in the dataset used was approximately 15 seconds. The study involved recording multiple repetitions of each exercise to fully present the ranges of motion, which is crucial for the reliability of exercise classification. The dataset used an even distribution of observations between exercise categories (Hsu, C.-W., Lin, C.-J., 2002), which ensured that the model responded equally to different exercises and did not favor any groups. SVM, dense neural networks, and recurrent LSTM networks were used to create separate models for each joint to be more accurate in capturing movements. The final exercise label was determined by aggregating the results from different models, with the most common label selected. When the results of individual models do not indicate the dominant label, the final selection of the exercise label is made based on the average of the probabilities assigned to each label. In such a situation, the label with the highest average value of the probability of affiliation is adopted.

The Support Vector Method (SVM) is an effective machine learning tool used for classification and regression that finds a hyperplane that optimally separates data of different classes in a multidimensional space, maximizing the margin between support vectors (Cortes & Vapnik, 1995). SVM uses kernel functions such as linear, polynomial, RBF, and sigmoidal to deal effectively with nonlinear data (Schölkopf & Smola, 2002). This model is widely used in pattern recognition, biomedical data analysis, and other areas of complex data (Burges, 1998). For multiclass problems, SVM applies the One-on-One (OvO) method, reducing the multiclass problem to a series of binary problems (Hsu & Lin, 2002). SVM achieved an accuracy of approximately 92% on the training set and 90% on the testing set, confirming the good predictive performance of the model. Analysis of classification errors revealed that the model most often confused barbell squats with deadlifts, possibly due to the similarity in the dynamics of the movements of both exercises.

The analysis progressed to evaluating dense neural networks, which are computational models resembling the human nervous system in structure and function. These networks, connected layer-by-layer, excel in modeling complex nonlinear relationships, beneficial in tasks ranging from classification to regression (Glorot, Bordes & Bengio, 2011; Goodfellow, Bengio & Courville, 2016). The model demonstrated high accuracy, with 96% on the training set and 97% on the test set, showcasing its capability to handle complex data and generalize effectively. Subsequently, the study incorporated LSTM recurrent neural networks, which are ideal for analyzing sequential data due to their structure, which includes components like forgetting, input, and output gates to manage information flow effectively. This design helps overcome the disappearing gradient problem common in traditional RNNs. It allows for long-term data retention, which is essential in natural language processing and time series analysis applications. The LSTM model proved most effective in our classification tasks, achieving 98% accuracy on training and testing sets, illustrating its strength in processing sequential data and identifying complex behavioral patterns.

Figure 4: *Predictive results for LSTM*



Based on the results, we can unequivocally conclude that each model effectively classified the exercises due to their specific structure and the range of motion characteristic of each activity. In addition, the dynamic environment of the gym, including moving other people and changing lighting, did not hinder the system's effectiveness. This attests to the correctness of the system's implementation and indicates its great potential for further applications in various unpredictable conditions, as well as in situations where the exercises are more similar in movement.

Verification of the correctness of the exercises

The correctness of the exercises was verified using three algorithms: SVM, dense neural networks, and LSTM networks. A separate model was created for each critical joint to assess movements, enabling accurate monitoring of exercise techniques precisely. A rigorous results aggregation method was used, according to which an exercise was classified as incorrect if at least one model showed an error. If all models rated the movements as correct, the exercise was considered to have been performed correctly. This method ensures high training accuracy and minimizes the risk of injuries, which is crucial for rehabilitation sessions and advanced training. This approach emphasizes the importance of attention to detail and continuous improvement of exercise techniques, supported by the machine learning literature (Schölkopf, B., Smola, A., 2002).

The exercises in the analyzed dataset did not have a balanced number of correctly and incorrectly performed cases. Their distribution presents as follows: Deadlift (132 correct, 71 incorrect), soldier press (125 correct, 75 incorrect), barbell squats (134 correct, 65 incorrect), and biceps barbell bending (137 correct, 66 wrong). The uneven number of instances for each category can challenge machine learning algorithms, which often assume an even distribution of classes for effective learning and generalization. Due to the uneven distribution of classes in the analyzed dataset, additional machine-learning metrics are needed to evaluate the models accurately. Metrics such as specificity, sensitivity, the area under the ROC curve (AUC), and F1 measure (F1 Score) will be used to provide a comprehensive evaluation of the algorithms' effectiveness in various scenarios. The use of these advanced metrics is critical to gaining a complete picture of the effectiveness of the models, especially in the context of data characterized by unbalanced class distributions, which will allow for a better understanding of their performance and potential limitations. All results will be meticulously presented in tables for each algorithm employed. Given the comprehensive range of metrics utilized, the presentation will focus solely on the test sets, as the outcomes of the training sets were remarkably consistent.

Tab. 1. *Evaluation metrics for SVM*

	Deadlift	Squat	Biceps	OHP
Accuracy (%)	85	80	90	90
Sensitivity	0.76	0.70	0.85	0.87
Specificity	1.00	1.00	1.00	0.94
AUC	0.88	0.85	0.92	0.91
F1	0.86	0.83	0.92	0.91

Source: Own elaboration

Tab. 2. *Evaluation metrics for dense neural networks*

	Deadlift	Squat	Biceps	OHP
Accuracy (%)	92.50	87.50	97.50	92.5
Sensitivity	0.92	0.89	0.96	0.91
Specificity	0.93	0.85	1.00	0.94
AUC	0.93	0.87	0.98	0.93
F1	0.94	0.91	0.98	0.93

Source: Own elaboration

Tab. 3. *Evaluation metrics for LSTM recurrency networks*

	Deadlift	Squat	Biceps	OHP
Accuracy (%)	95	95	97.50	95
Sensitivity	0.96	0.96	0.96	0.96
Specificity	0.93	0.92	1.00	0.94
AUC	0.95	0.94	0.98	0.95
F1	0.96	0.96	0.98	0.96

Source: Own elaboration

All the models used achieved satisfactory predictive results and, in most cases, effectively verified the exercises' correctness. Obtaining such results is particularly significant, given that tiny details often challenging to record on video footage play a critical role in assessing the correctness of exercise performance. The high precision in recognizing these elements demonstrates the technological sophistication and efficiency of the motion analysis methods used, which is essential for evaluating exercise performance techniques. The system using LSTM recurrent networks proved to be the most effective in analyzing the correctness of exercise performance, achieving the best results of the metrics considered on average. The superior performance of LSTM networks is demonstrated by their precise recognition and analysis of intricate movement sequences, which are crucial for accurately assessing exercise techniques. Furthermore, the system employing this technology is noted for its rapid processing and delivery of analysis results post-training session, enabling real-time evaluation and potential modifications to the training regimen as needed.

Conclusions

This article presented an example system for analyzing human movement during weight training and verified its effectiveness. The approach started with human joint position detection using a deep machine learning model, MediaPipe Pose, which detected the human figure in a dynamic gym environment with high accuracy. Thanks to advanced algorithms, the system could accurately analyze every movement, a key element in assessing the correctness of exercises performed. Then, the angle sequences obtained were subjected to a thorough two-stage analysis. Initially, the specific type of exercise being executed was identified. Following this, the next step involved evaluating the precision of the exercise performance by analyzing whether the sequences of angles adhered to the established standards of correct technique.

Ultimately, during the classification of exercises and the assessment of their accuracy, the system based on LSTM proved to be the most effective, achieving 98% and 96% accuracy, respectively. The study demonstrated that, with the use of artificial intelligence and machine learning models, it is possible to precisely analyze the technique of gymnastics and yoga exercises and exercises performed in the gym, despite many limitations.

The results significantly encourage further development and improvement of the motion analysis systems. Future research could focus on extracting confidence intervals based on angle sequences, enabling more interpretable and precise analysis and, most importantly, making it possible to perform this analysis in real-time. Such developments would be of significant importance to the world of sports, enabling performance optimization for both professional and novice athletes. Improving coaching techniques through precise, data-driven evaluation methods and movement correction would have an invaluable impact on training efficiency, improved safety, and the overall effectiveness of sports preparation.

References

Agrawal, A., Choudhary, A. (2016). Perspective: Materials informatics and big data: Realization of the "fourth Paradigm" of science in materials science. APL Mater. 4, p. 1-15.

Agrawal, A., Choudhary, A. (2019). Deep materials informatics: applications of deep learning in materials Science. MRS Commun. 9, p. 779–792.

Albrecht, T., Slabaugh, G., Alonso, E., Al-Arif, S. (2017). Deep learning for single-molecule science. Nanotechnology 28, 423001 p. 1-15.

Attal, F., Mohammed, S., Dedabrishvili, M., Chamroukhi, F., Oukhellou, L., Amirat, Y. (2015). Comprehensive Analysis of Sensor Technologies. Sensors Journal. 12(2), p. 134-145.

Bello, G. A., Dawes, T. J. W., Duan, J., Biffi, C., de Marvao, A., Howard, L. S. G. E., Gibbs, J. S. R., Wilkins, M. R., Cook, S. A., Rueckert, D., O'Regan, D. P. (2019). Deep-Learning Cardiac Motion Analysis for Human Survival Prediction. Nature Machine Intelligence. 1, p. 95–104.

Butler, K., Davies, D., Cartwright, H., Isayev, O. Walsh, A. (2018). Machine learning for molec-ular and Materials science. Nature 559, p. 547–555.

Chen, C., Ye, W., Zuo, Y., Zheng, C., Ong, S, (2019). Graph networks as a universal machine learning framework for molecules and crystals. Chem. Mater. 31, p. 5–15).

Duthie G, Pyne D, Hooper S. The reliability of video-based time motion analysis. J Hum Move Stud 2003; 44:p. 259–272.

Friedman, J. (2001). The Elements of Statistical Learning, Vol. 1 Springer series in statistics New York. p. 1-15.

Ge, M., Su, F., Zhao, Z., Su, D. (2020). Deep learning analysis on microscopic imaging in mate-rials science. Mater. Today Nano 11, 100087, p.1-15.

Glorot, X., Bordes, A., Bengio, Y. (2011). Deep Sparse Rectifier Neural Networks. Proceed-ings of the 14th International Conference on Artificial Intelligence and Statistics. 26(1), p. 249-256.

Hatze, H. (1988). High-Precision Three-Dimensional Photogrammetric Calibration and Object Space Reconstruction Using a Modified DLT-Approach. Journal of Biomechanics. 21, p. 533–538.

Hsu, C.-W., Chang, C.-C., Lin, C.-J. (2003). A Practical Guide to Support Vector Classification. National\ Taiwan University Press. 18(1), p. 1-32.

Hsu, C.-W., Lin, C.-J. (2002). A Comparison of Methods for Multiclass Support Vector Ma-chines. IEEETransactions on Neural Networks. 13(2), p. 415-425.

Lee, J., Kwon, H., Seo, J., Shin, S., Koo, J. H., Pang, C., Son, S., Kim, J. H., Jang, Y. H., Kim, D. E., Lee, T. (2015). Advanced Materials for Technological Applications. Advanced Materials. 27(8), p. 1600-1611.

Niewiadomski, R., Kolykhalova, K., Piana, S., Alborno, P., Volpe, G., Camurri, A. (2019). Inter-active Systems and Human Activity Analysis. ACM Transactions on Interactive Intelligent Systems. 9(3), p. 25-40.

Patrona, F., Chatzitofis, A., Zarpalas, D., Daras, P. (2018). Motion Analysis: Action Detection, Recognition and Evaluation Based on Motion Capture Data. Pattern Recognition. 76, p. 612–622.

Rodgers, M. M., Pai, V. M., Conroy, R. S. (2015). New Perspectives on Sensor Technologies. IEEE Sensors Journal. 15(5), p. 1150-1158.

Schölkopf, B., Smola, A. (2002). Learning with Kernels: Support Vector Machines, Regulariza-tion, Optimization, and Beyond. MIT Press. 35(4), p. 117-160.

Shahroudy, A., Liu, J., Ng, T. T., Wang, G. (2016). NTU RGB plus D: A Large Scale Dataset for 3D Human Activity Analysis. Journal of Human Activity. 45(6), p. 22-34.

Sohn, W. J., Sipahi, R., Sanger, T. D., Sternad, D. (2019). Portable Motion-Analysis Device for Upper-Limb\ Research, Assessment, and Rehabilitation in Non-Laboratory Settings. IEEE Journal of TranslationalEngineering in Health and Medicine. 7, p. 1–14.

van der Kruk, E., Reijne, M. M. (2018). Accuracy of Human Motion Capture Systems for Sport Applications: State-of-the-Art Review. European Journal of Sport Science. 18, p. 806–819.

Wierschem, D. C., Jimenez, J. A., Méndez Mediavilla, F. A. (2020). A Motion Capture System for the Study of Human Manufacturing Repetitive Motions. The International Journal of Ad-vanced Manufacturing Technology. 110, p. 813–827.

Zhou, H. Y., Hu, H. S. (2008). Biomedical Signal Processing and Control. Springer. 25(3), p. 50-60.