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Validation and Performance Analysis of a Technique for Suggesting Corrective Indices and Measures in Exercise Execution

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ABSTRACT

Recent advancements in posture estimation, action recognition, and motion prediction enable detailed analysis of motions, hence facilitating the identification of possible errors during exercise. This research examines the validity and performance evaluation of a method designed to recommend corrective indices or measurements for lower-body workouts, namely squats. This project involves the compilation of a dataset of films, as well as 2D and 3D representations of both right and wrong executions of various activities, namely squats, lunges, planks, and pickups. The study employs datasets from many squat types, including bodyweight squats, goblet squats, and pistol squats, among others. The suggested method examines motion patterns and detects deviations from the optimal performance of each squat variant using sophisticated motion detection algorithms and machine learning. The technique's efficacy is assessed by juxtaposing its remedial recommendations with expert human evaluations, yielding insights into its correctness, efficiency, and applicability. This research investigates the efficacy of corrective indicators to improve exercise performance, avert injuries, and facilitate successful training. The results highlighted the technique's effectiveness, with 97% of squats and 100% of planks being correctly classified post-correction, showcasing its capability to enhance performance and prevent injuries. The classification accuracy for squats and lunges was not perfect, with 60% accuracy for squats and 83% for lunges, indicating areas for further improvement.

Keywords: *Posture Estimation; Action Recognition; Corrective Index; Motion Prediction.*

1. INTRODUCTION

In recent years, the emergence of fitness technology and motion detection systems has revolutionized the analysis and enhancement of exercise performance. Correct exercise technique is essential for optimizing workout efficacy and reducing injuries.

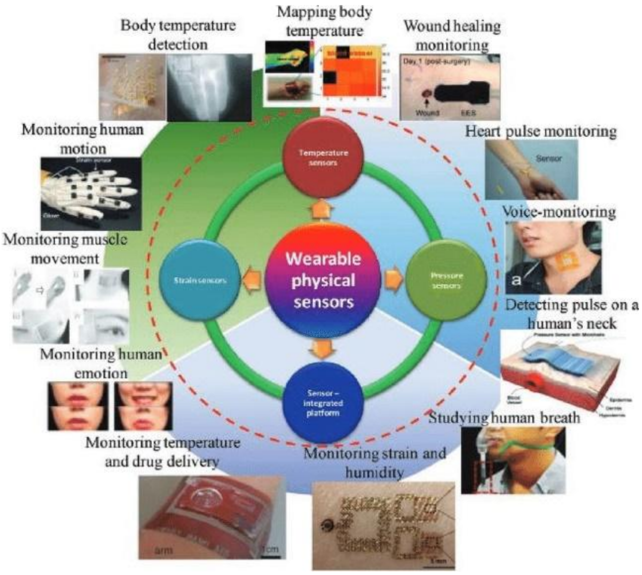

Figure 1. Overview of the different applications of wearable flexible sensors[1]

Squats are among the most often executed workouts for fortifying the lower body, focusing on muscles like the thighs, glutes, and calves. Although squats provide significant advantages, incorrect technique may result in injury or training ineffectiveness. Consequently, it is essential to establish techniques for identifying variations from optimal squat form and suggesting correction measures. Notwithstanding the widespread popularity of squat workouts, there exists a deficiency in effective methods for real-time analysis of squat performance and the provision of remedial feedback. Current methodologies depend on manual observation or broad norms, which often lack consistency and objectivity (Gama et al., 2019).

This study seeks to design a motion correction algorithm that can provide a corrected version of a given movement (Sun et al., 2017). This allows the patient to acknowledge their error by reviewing the fix and identifying ways to enhance their practice.Compile a dataset including accurate and inaccurate iterations of the same maneuver. Subsequently, use this dataset to construct a motion correction model and assess its efficacy using an action recognition model trained on the same dataset. Ultimately, include motion correction model in a pipeline that processes raw video pictures to provide corrected movement. Next section explains literature review.

2. LITERATURE REVIEW

This literature review examines improvements in exercise form correction, including pose estimation in squats and correction models for squat variations.

Table 1. Literature survey of existing methods

Author and Year	Methodology	Key Findings
Tsamardinos et al. (2017)	Cross-Validation (CV), Bootstrap Bias Corrected CV (BBC-CV), and Bootstrap Bias Corrected with Dropping CV (BBCD-CV). The study focused on identifying optimal configurations for predictive models.	BBC-CV outperformed traditional cross-validation by reducing bias and variance, and improving computing efficiency. The approach used out-of-sample predictions and bootstrapping to identify optimal model configurations. BBCD-CV provided more precise performance estimates while reducing the need for re-training models.
Mathai et al. (2019)	Computational methods for target prediction (molecular similarity, network-based approaches, machine	Emphasized the need for robust validation techniques for target prediction, especially for bioactive

[1] figure/An-overview-of-the-different-applications-of-wearable-flexible-sensors-99-Courtesy-of_fig12_322235592

	learning, and docking). Statistical validation of retrospective data for target prediction.	molecules. The study proposed adding more performance dimensions to improve the accuracy of predictive models. It critiqued the lack of comprehensive prospective experiments and discussed limitations in generalizing performance based on bioactivity data.
Raza et al. (2023)	Human position and gesture estimation using computer vision and machine learning. Logistic Regression Recursive Feature Elimination (LogRF) for feature selection and random forest for performance evaluation.	Developed an AI-based solution for human position estimation in physiotherapy and fitness, improving real-time analysis of exercise form. The study demonstrated that using top features from skeletal movement data improved performance (0.998 accuracy). This approach helped in identifying and correcting biomechanical issues, crucial for injury prevention and training enhancement.
K and Vincent, (2024)	GCN-XGBoost with an attention mechanism for workout detection using 2D posture coordinates from the MMFit dataset. Used XGBoost for detecting postural deviations in exercises.	The model achieved 98% accuracy in detecting correct and incorrect squat forms. The research showed the potential of using XGBoost and computer vision in real-time feedback for workout correction. The model relied on 2D skeletal data to classify various exercises and provide corrective feedback, enhancing fitness and rehabilitation processes.

This research aims to fill the gaps noted in the current literature, including the need for real-time, effective corrective measures for various exercises. The objective is to evaluate and assess a method for detecting abnormalities in form during exercise execution and to provide specific correction measures that might improve performance and reduce injury risk. Next section explains the methodology.

3. METHODOLOGY

Recent advancements in posture estimation have enabled numerical automated exercise correction tasks to transition from relying on numerous sensors, such as accelerometers or gyroscopes, to using publicly available datasets and vision-based systems. Certain applications are designed to identify fitness routines and tally repetitions; however, they often do not include real-time feedback and correction on workout performance. Discrepancies between a goal posture and that of the participant doing the exercises have been examined for both 2D and 3D poses using open-source pose estimation tools.

Dataset

Within the scope of this study, a dataset was curated by combining accurate and inaccurate renditions of various physical workouts, performed by individuals under diverse conditions. The dataset includes a range of common exercises such as squats, lunges, planks, and pick-ups. Publicly available visual sources such as Kaggle and Pexels were referenced to assemble a heterogeneous and realistic training corpus. The following sections elucidate the processes of data refinement and labeling.

Data Acquisition

Visual content used in the study was sourced from public datasets and verified repositories that provide open-access fitness footage. The selected content includes high-resolution videos demonstrating both correct and incorrect techniques for each exercise type. Sampling was standardized at 30 frames per second, with frame resolution preserved at full HD (1920 × 1080 pixels). Exercises were identified, segmented, and annotated based on visible posture deviations as seen in figure 2.

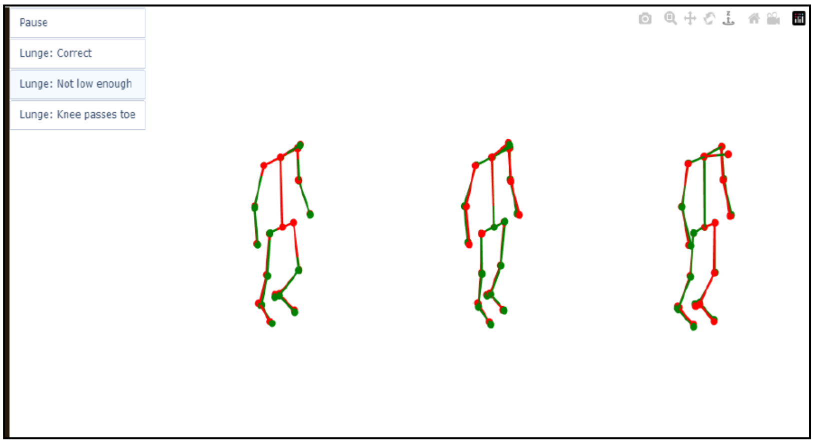

Figure 2. Sketches of actions

The exercises included are:

1. Squats: Upright descent of hips and return
2. Lunges: One leg stepped forward, flexed knee
3. Planks: Linear posture with arms and toes on ground
4. Pick-ups: Bending down to lift and place an object

Individual Movements

Now isolate individual repetitions. For squats and lunges, this is accomplished by measuring the vertical distance between the most distant joints (x-coordinate) in the 2D position. Assuming these activities start and conclude in a standing posture, the two joints are presumably situated in the head and the feet. In relation to the plank exercise, use the first discrete derivative of knee height over time as a criteria for separation, as participants lower their knees between each motion. The values are graphed over time and subjected to mean filtering (Diller et al., 2022). Conversely, in the pick-up exercise, it is infeasible to isolate individual motions, since participants execute the job not varying ways; some maintain continuous grasp of the cube, while others set it down between moves. Consequently, have opted not to categorize them and will proceed only with SQUATs, lunges, and planks (Gupta et al., 2023).

Table 2. The parameters for filter size and peak detection

Action	Filter Size	Minimum peak height	Minimum peak distance
SQUATs	20	550	45
Lunges	20	550	60
Planks	15	1.5	100

Motion Correction

Prior to training any motion correction architecture, the information acquired and refined in preceding sections is restructured into an array of dimensions 3J x L, where J denotes the number of chosen joints, L signifies the number of frames in the sequence, and 3 corresponds to the xyz coordinates. At this stage, some joints (namely the eyes, ears, and little toes) are eliminated, since their impact on motion accuracy is anticipated to be negligible or minimal. Furthermore, each erroneous action is linked to a corresponding right action as the ground truth. As sequences may vary in length, they are first aligned by 2D Dynamic Time Warping (DTW).

$$x_k = \sum_{l=0}^{L-1} s_l \cos\left[\frac{\pi}{L}\left(l+\frac{1}{2}\right)k\right], \quad (1)$$

$$s_l = \frac{1}{\sqrt{2}}x_0 + \sum_{k=1}^{K-1} x_k \cos\left[\frac{\pi}{L}\left(l+\frac{1}{2}\right)k\right] \quad (2)$$

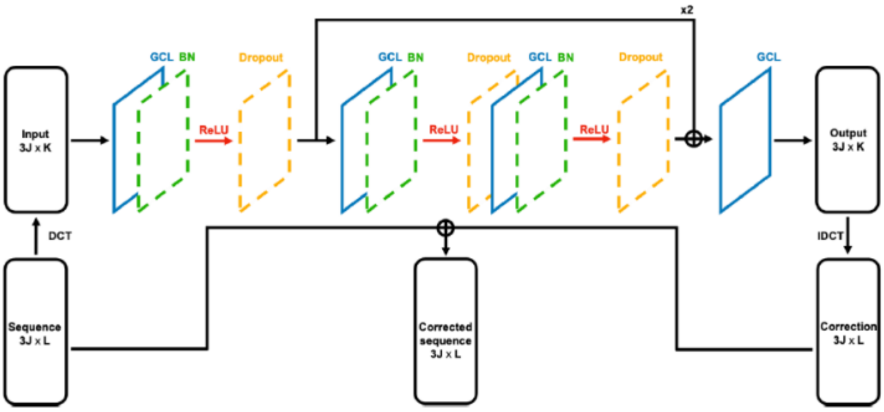

Figure 3. Correction model architecture

The architecture indicates that the output retains the same dimensions as the input and signifies the adjustments required for each joint coordinate (Du et al., 2021).

Action Recognition

To evaluate the efficacy of motion correction model, suggest the development of a motion classifier capable of distinguishing between action types and movement accuracy (Grewe et al., 2022). The design of this model, seen in figure 4, is clearly derived from the correction model devoid of residual blocks, including a linear output layer with a LogSoftMax activation function and a hidden size of 32.

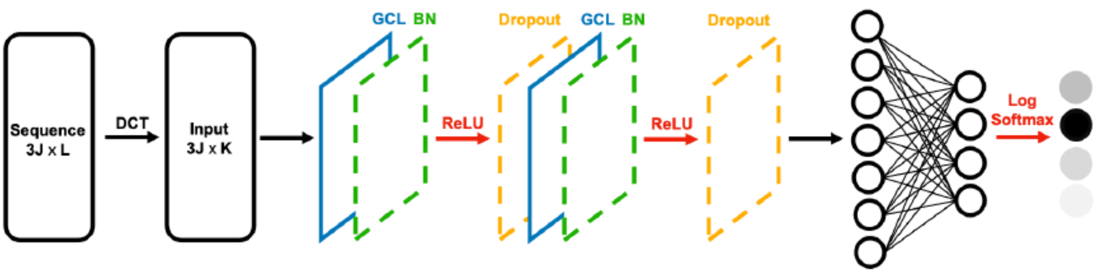

Figure 4. Classification Model Architecture

4. RESULT ANANLYSIS AND DISCUSSION

The clap was used to synchronize all four videos. Subjects S0, S1, S2, and S3 correspond to subject 0, 1, 2, and 3, respectively, each performing the instructions for the specified action as outlined in Table 1.

Figure 5. Samples images. Images of 4 subjects: (A) Subject 0 performing a SQUAT viewed from camera 6_1, (B)

Subject 1 performing a lunge viewed from camera 6_2, (C) Subject 2 doing the plank viewed from camera 6_3, (D) Subject 4 picking-up the box viewed from camera 6_4.

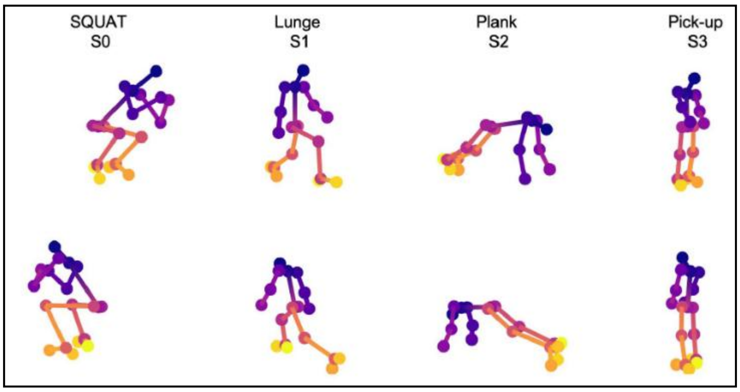

Figure 6. Sample 3D Pose estimations

Estimated 3D poses obtained from the 2D poses displayed in figure 8. Top and bottom are the same poses observed from a different angle. The average length of a movement is 79, 100 and 58 frames for SQUATs, lunges and planks, respectively (Cavalcanti et al., 2019).

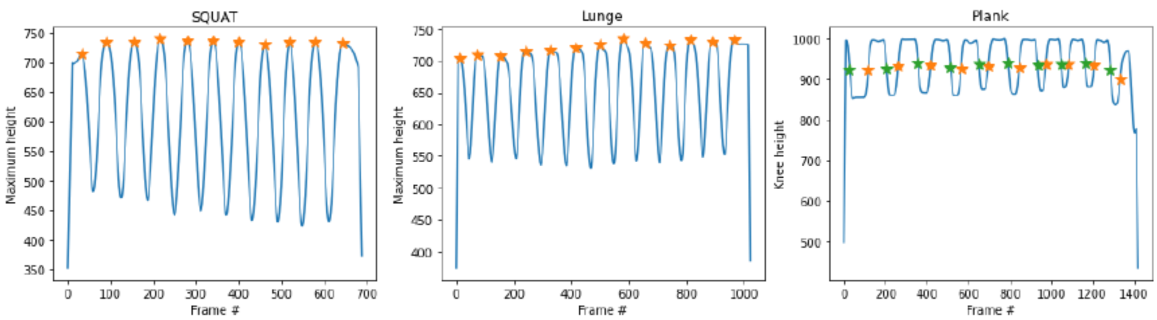

Figure 7. Individual movements separation plots

Motion Correction

When all the movements have been labeled, sequences of 3D poses are fed to the motion correction model described. Qualitative results of this model on the test subject (number 3) for every instruction are shown in figure 10.

Table 3. Classification model results on corrected movements.

Action	Instruction	Correct	Incorrect	Accurately corrected	
SQUATs	Correct	10	0	100%	
					97%
	Feet too wide	5	0	100%	
	Knees inward	5	0	100%	
	Not low enough	4	0	100%	
	Front bent	6	1	86%	
Lunges	Correct	11	1	92%	64%
	Not low enough	1	10	10%	
	Knee passes toe	9	1	90%	

Planks	Correct	7	0	100%	100%
	Arched back	9	0	100%	
	Hunch back	9	0	100%	

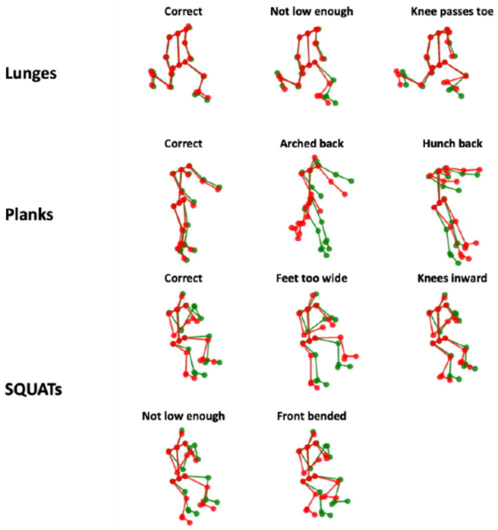

Figure 8. Qualitative results of correction model.

The dataset generated in this project consists of 363 individual movements, each defined by 3D pose re-projection from all four cameras and one 3D pose sequence. The corrections applied to incorrect movements effectively guide them toward the correct form. However, improvements are still needed, particularly in arm correction during squats. One hypothesis for this issue is the insufficient number of correct squat examples to capture the full variability of arm movements during the action. The motion classifier provides a more quantitative assessment of the correction performance. The classification accuracy for correct squats and lunges is 60% and 83%, respectively. Specifically, three squats are incorrectly classified as not low enough, and one is classified as front-bent. However, after correction, 97% of squats and 100% of planks are correctly classified, indicating that the correction process is largely effective.

5. CONCLUSION

This research successfully validated and performed a comprehensive analysis of a technique designed to suggest corrective indices and measures for executed exercises, specifically focusing on lower-body movements such as squats and lunges. The proposed method, utilizing advanced motion detection algorithms and machine learning, demonstrated its potential in identifying and correcting errors in exercise execution. The results highlighted the technique's effectiveness, with 97% of squats and 100% of planks being correctly classified post-correction, showcasing its capability to enhance performance and prevent injuries.

However, the classification accuracy for squats and lunges was not perfect, with 60% accuracy for squats and 83% for lunges, indicating areas for further improvement. Specifically, arm correction during squats showed potential for optimization, possibly due to the limited number of correct squat examples in the dataset. These findings emphasize the importance of refining the motion classifier and expanding the dataset to capture a wider variety of correct movement patterns.

Overall, this study paves the way for more accurate and efficient exercise correction techniques that can be integrated into fitness and rehabilitation settings, contributing to safer training environments and improved outcomes for users. Further research is needed to fine-tune the system and enhance its generalizability across different exercises and populations.

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