

THE IDENTIFICATION OF KNEE DEVIATION DURING THE SQUAT MOVEMENT

Vikranth Nara and Jason Park

Rock Ridge High School Ashburn, Virginia, USA

DOI: 10.46609/IJSSER.2022.v07i09.022 URL: <https://doi.org/10.46609/IJSSER.2022.v07i09.022>

Received: 25 September 2022 / Accepted: 3 October 2022 / Published: 7 October 2022

ABSTRACT

This paper describes software to evaluate the ideal form to prevent injury and promotes muscle growth when squatting. The software spots if any excessive knee internal rotation or abduction is occurring. For model creation, we took Tensorflow's Body Pix model and performed 3-dimensional pose segmentations and used those coordinates in another model to correctly classify the user's squatting form as either too far or too inward in terms of deviation. Specifically, we created a multi-variable regression model that connects these points in the XYZ plane that was trained on the resulting coordinates from the pre-trained pose estimation model used on a custom dataset of YouTube videos from power lifting competitions. Then, we modeled Euclidean distance, 3d angles, and depth value through equations to evaluate the bend and distance between the hip, knee, and ankle for targeting left and right deviation by specifying 3 stages: going down, middle squat, and going up.

Purpose

The primary purpose of this project was to develop a model that would be able to prevent injuries, specifically patellofemoral joint pain, in people performing squats by highlighting issues in the position of the knees while squatting.

Background

There is a recent trend pointing toward an increased interest in weightlifting, and weighted squatting has been popularized by the general population as it is ideal for developing the quads, hip flexors, and glutes (Leyland, 2007). However, they also can contribute to irreparable damage to the knees because shear forces are multiplied through the extra weight and pressure the body must lift. Improper placement of the knees can happen through many variables. However, the most prominent are: weak internal and external rotators in the hip, weak muscles that surround

the knee joint (quads, hamstrings, calves), and weak hip extensors. These muscles are vital for squatting with proper biomechanics and keeping the legs straight with no awkward bends to increase shear loads. However, when these muscles are weak or are dominated by other muscles, the legs do not function as they should. This application can also act as a test bed for other exercises including the bench press and the deadlift, which are among the most common injury-prone exercises. For instance, we create a multi-regression model trained on videos of real people in different natural environments in consistent situations. The variance inflation factor was then used to analytically evaluate variables in the environment that had an impact on the person's form and performance of their squat. By using vector formulas to calculate the weight and forces distribution in the knee, we can maximize performance by guiding new users to move up or down in the amount of weight being lifted while still considering the risk of injury and comfortability of the user.

Patellofemoral joint pain is a type of pain that occurs behind the patella. This type of pain occurs from the repetition of improper movement of the knee. The meniscus is a fibrocartilage that sits between the femur and the tibia. It is vital for the cushioning and mobility of the human knee as it is capable of handling large loads of weight. While shear forces may apply to daily activities such as running and walking, the forces are multiplied when weight training. Weightlifting is being used as a test for our innovative system as the implications reach from sports to health & fitness.

Related Work

Ogata, R., and al. (2019) present an action dataset of videos where good and bad form are included with 6 different categories for poor form: inward knees, round back, warped back, upwards head, shallowness, and frontal knee. Data was extracted from individuals from varying scenes, and videos on YouTube. The approach was similar to our application with both software utilizing 3D Pose Estimation and distance matrices. However, the difference lies in that this dataset uses people who are doing only bodyweight exercises and not exercises with weights such as dumbbells or barbells. This causes a discrepancy in measurements and tensions in one's body. In addition, this dataset utilizes a convolutional neural network to sort the data and uses a one-dimensional convolution to classify the data. This model achieves an accuracy of 75% when classifying bodyweight squats (128 frame inputs).

Chen, Y., and al. (2019) propose a real-time system called Fitness Done Right (FDR) to classify bodyweight planks or squats. Similar to the previous system, FDR begins with pose estimation to retrieve the coordinates of the targeted joints where the data was taken from frames of videos in the 2nd dimension. The detection model combines the use of Euclidean and angle distances to determine plank or squat and if the user is bending their knees to the benchmark set at 90 degrees.

Additionally, the flow chart illustrates that, for the squats, the body weight needs to be distributed correctly to the heels. However, FDR failed to properly scale each frame as a 2d picture and compare it to 3d coordinates, distorting the 3D dimension. This system utilized a two-branch Convolutional Neural Network(CNN) with multidirectional recognition, and this resulted in a recognition error rate of 1.2%.

Hannan et al. (2021) suggest wearable technology with an accelerometer, gyroscope, and EMGs (electromyography sensors for the activity of bicep and back muscles) to receive data from two exercises that were tested: T-bar and bicep concentrated dumbbell curl. 7 features were notably important: delta x, delta y, delta z, relative radial distance, angular distance, mean absolute value, and root mean square. The featured data from the sensors are inputted into the KNN (k-nearest neighbors algorithm) and 3 predictions (recommendations) are outputted based on the classified exercise: perfect form (prediction 2), straighten the lower back and lift your chest (t-bar)/must rest(plank)(prediction 3), and please bend a little(prediction 4). KNN had an 89% accuracy while using the forward feature selection technique.

Chen, S., and al. (2020) introduced Pose Trainer, an application based on pose estimation and visual geometry. This provides personalized recommendations for improvements in the user's form in 4 exercises: bicep curl, front raise, shoulder shrug, and shoulder press. A dynamic time warping for sequence classification model was trained on over 100 exercise videos (custom dataset of recorded videos) of correct and incorrect forms based on geometric-heuristic algorithms. Then, similar to previous papers, Euclidean distances were calculated. The average precision between all four exercises was 0.89, the recall was 0.86, and the F1 Score was 0.86.

A study led by Yoshinori Kagaya, Yasunari Fujii, and Hidetsugu Nishizono (2013) shows a correlation between ACL injuries with dynamic knee valgus. Kagaya recruited 130 female basketball players for this experiment and observed the athletes' movement of the knee in conjunction with their hips and feet. In short, knee valgus is the inward bending of the knee, which means that the knee itself is closer to the center of the body than the hip and feet are. The knee-in distances (KOD) and hip-out distances (HOD) were measured to determine the valgus. The athletes with KOD and HOD present were at higher risk of ACL injury. Kagaya explains that with more KOD and HOD present, more forces are applied to the actual knee joint itself as the pressure is built up in a variety of directions. Kagaya had found through this experiment and a prior experiment by Hewett et al. (2001) that athletes that had ACL injuries more often had knee valgus. These injuries could be prevented through more activation of the hip abductor and foot alignment while performing a squat (Kagaya, Fukii, Nishizono, 2013).

Methods and Procedures for Creating the Present Software

Materials Used in Training the Software/IV-DV

- Arnold Powerlifting Sports Festival 2017, 2018, 2019 (Over 100 videos of individual people)
- Arnold Powerlifting Sports Festival 2007-2021
- Tensorflow with Pose Estimation, Prebuilt Tensorflow Model

[https://www.tensorflow.org/lite/examples/pose_estimation/overview].

Independent Variable: Individual Lifters

Dependent variable: 3D Deviation of the knee with respect to the ankle and the shoulder, which is measured by a metric called the R^2 value

Procedures

Part 1: Prepping Tensorflow Model for running on the Arnold 2007-2021 competitions

1.1 Download and extract Tensorflow prebuilt segmentation model (3d Pose Estimation) from https://www.tensorflow.org/lite/examples/pose_estimation/overview

1.2 Follow the direct instructions given by Tensorflow (https://www.tensorflow.org/lite/tutorials/pose_classification) to extract and use this model in real-time

1.3 Utilize Open CV by feeding each frame into the TensorFlow pose estimation model

Part 2: Preprocess custom dataset of Arnold 2007-2021 competitions into a more usable format

2.1 Download the .mp4 files and edit the video so that each squat is a different file (This will allow for the regression model to work accurately)

2.2 Manually go through the individual videos and create a .xlsx file that stores the file path of each video and if the person that squatted in the video has good or bad form (1 for good form and 0 for bad form) in the same row

2.3 Repeat steps 2.1 and 2.2 for all the 2007 - 2021 Arnold Competitions

Part 3: Create a dataset for the regression model

3.1 Iterate through the .xlsx file to extract the file path that contains the video that will be run through using TensorFlow's pose estimation model to get the coordinates of the knee, hip, and ankle

3.2 Store these coordinates into another file called data.xlsx

3.3 Run through the coordinates to find out the lowest y-value point, which represents the depth the user went into their squat. Separate the squat into 3 stages (going down, low point, and going up).

3.4 Write vector distance, vector intersection, vector projection, and vector angle methods using 3-dimensional vector math from our 3-dimensional coordinates

3.5 Repeat the following steps for the downward stage and the upward stage

3.6 Take the coordinate points in data.xlsx and iterate through each row and then pass those hip, knee, and ankle coordinates into the vector angle method to get the 3d degree bend of the left and right knee.

3.7 Pass the coordinates into the vector projection method and then pass the output of that method into the vector intersection to get the deviation of the left and right knee with respect to the line between the hip and the ankle

Part 4: Create the regression model and test it

4.1 Create a train-test split with the 70:30 ratio using the sci-kit learn library

4.2 To create the multiple linear regression model in the sci-kit learn library (https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html)

4.3 To test the model, use the sci-kit learn library to test it

Characteristics of Training Materials

Data Tables & Graphs

Table 1. Dataset Origination

Dataset	Individuals Participated	Videos Used
Good Form - YouTube (Arnold Competitions)	243	354
Bad Form - Pre-existing Dataset	3	243

Table 2. Dataset Classification

	Train	Test	Total
Good Squat	213	141	354
Inward Knee Squat	76	56	132
Uneven Knee Squat	63	48	111
Total	352	245	597

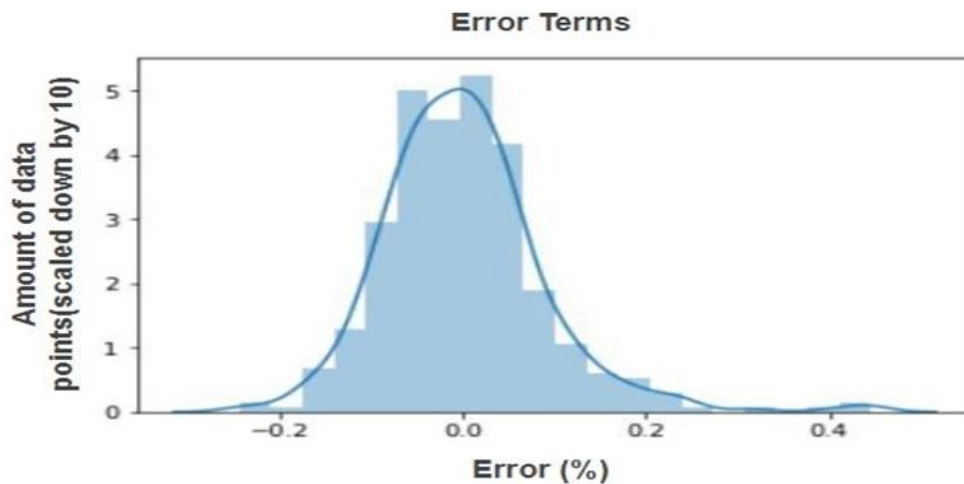
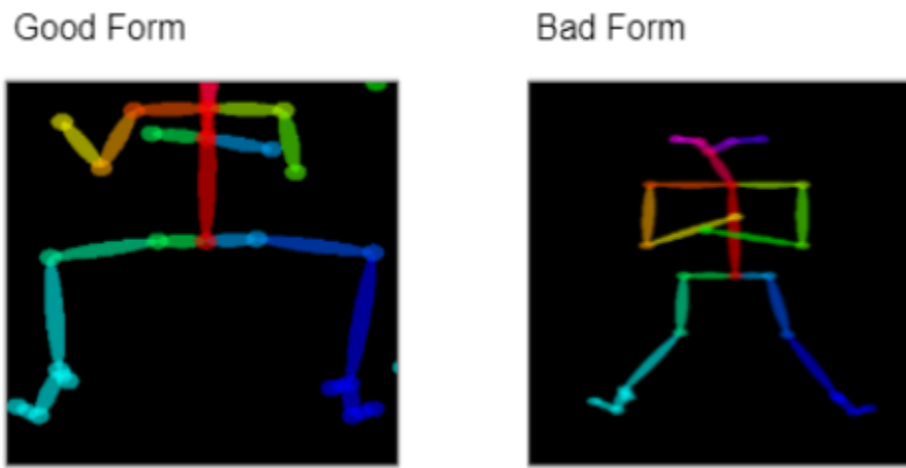


Figure 1. Histogram of the mean of the residual analysis of the train/test data. The x-axis represents the amount of error and the y-axis represents the amount of data scaled down by a factor of 10.



Figures 2a and 2b. Images of the model working on good and bad form

Results/Data Analysis

Our model's R^2 value stayed around .79, meaning the regression equation that was calculated according to our dataset fit well for the training set that was given. This value was higher than expected. Our datasets were almost self-made, which meant that our data had lots of different factors that could affect our model. However, our model stayed consistent. With this model, we will be able to find the knee deviation of a squatter and determine whether or not the squat is healthy or risky for the squatter's knees with somewhat high consistency. However, a residual analysis must still be considered to ensure that the regression model did not overfit.

We used 597 videos of good and bad forms from various powerlifting competitions containing all weight classes of both genders. Our system detected coordinate points and our application analyzed 3D distances and angles between the hips, knees, and ankles to be able to calculate if the person has good or bad form. Then, we drew the outputted segmentation that is desired to be the perfect form. Other squats will be compared to this perfect form. Typically, when our model was able to detect poor form, we found that the knees were inwardly bent. This data shows that our model fits our prediction that when the knees are put out of alignment with the rest of the body through improper muscle activation, the form can be concluded as improper. The data was also able to align with the parameters that we had set for proper knee location, which means that our model was able to properly perceive what good form is.

Possible Data Gaps

Our R^2 value of .79 was higher than expected, as there were many extra factors in our dataset when we ran our model through the videos. While this may be true, an R^2 value of .8-.9 would

have been preferred as that would have meant our data would better fit the parameters that we created. Possible gaps that limited our R^2 value would have been the various datasets that we had used. Our datasets were self-made, which made it difficult to properly train the model from the start due to the vast number of different settings that the squatters were performing in. In addition to this, our dataset did not have as many videos as we had hoped because of the limited amount of data we had.

Another limitation of our experiment was the multitude of factors that were involved in judging whether an individual's squat was good or bad. Because of this, it made weighing certain variables over another difficult because every variable contributes to the form of a squat. In doing this, we ended up weighing certain variables much more than others, causing some to be neglected. The few that were neglected could have contributed to a higher R^2 value if they had been accounted for. However, the variables that were disregarded could have been used if we had a larger dataset.

Moving Forward

As we move forward with this project, we hope to collect large amounts of data from all angles and increase the amount of data that we can run our model through. We would also like to add a way for our model to scan through the entire body while squatting to detect full-body imbalances or mistakes while squatting. In addition, further analysis of our data has been considered so that we can make our model more accurate. These analysis factors would include: residual analysis, variance inflation factor, and recursive feature elimination to validate the importance of the data. For releasing our model to the public, we would like to spread our model to large fitness industries, personal trainers, and physical therapists to make squatting more accessible for all.

Furthermore, we would like to spread our model to the general public by being able to implement our model in a real-time camera and phone application. Lastly, we would like our model to be able to tell in real-time the specific issues of a squat rather than naming only if the squat is good or bad.

References

Amin, R. M., Andrade, N. S., & Neuman, B. J. (2017). Lumbar Disc Herniation. *Current reviews in musculoskeletal medicine*, 10(4), 507–516. <https://doi.org/10.1007/s12178017-9441-4>

Chen, S.; Yang, R.R. Pose Trainer: Correcting exercise posture using pose estimation. arXiv 2020, arXiv:2006.11718.

Chen, Y., Chen, Y., & Tu, Z. (2019). Fitness Done Right: a Real-time Intelligent Personal Trainer

for Exercise Correction. arXiv preprint arXiv:1911.07935.

Fares, M. Y., Fares, J., Salhab, H. A., Khachfe, H. H., Bdeir, A., & Fares, Y. (2020). Low Back Pain Among Weightlifting Adolescents and Young Adults. *Cureus*, 12(7), e9127. <https://doi.org/10.7759/cureus.9127>

Fry, A. C., Smith, J. C., & Schilling, B. K. (2003). Effect of knee position on hip and knee torques during the barbell squat. *Journal of strength and conditioning research*, 17(4), 629–633. [https://doi.org/10.1519/1533-4287\(2003\)017<0629:eokpoh>2.0.co;2](https://doi.org/10.1519/1533-4287(2003)017<0629:eokpoh>2.0.co;2)

Hannan, A.; Shafiq, M.Z.; Hussain, F.; Pires, I.M. A Portable Smart Fitness Suite for Real-Time Exercise Monitoring and Posture Correction. *Sensors* 2021, 21, 6692. <https://doi.org/10.3390/s21196692>

Kagaya, Y., Fujii, Y., & Nishizono, H. (2015). Association between hip abductor function, rear-foot dynamic alignment, and dynamic knee valgus during single-leg squats and drop landings. *Journal of Sport and Health Science*, 4(2), 182–187. <https://doi.org/10.1016/j.jshs.2013.08.002>

Leyland, T.L. (2007). The Crossfit Journal Articles, Spine Mechanics for Lifters, 63, 1-5, https://www.lbs.co.il/data/attachment-files/2012/02/6975_63_07_Spine_MechanIcs.pdf

Ogata, R., Simo-Serra, E., Iizuka, S., & Ishikawa, H. (2019). Temporal Distance Matrices for Squat Classification. 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2533-2542.

Salem, G. J., & Powers, C. M. (2001, May 30). Patellofemoral joint kinetics during squatting in collegiate women athletes. *Clinical Biomechanics*. Retrieved February 11, 2022, from https://www.sciencedirect.com/science/article/pii/S0268003301000171?casa_token=YX1GY0cJBxkAAAAA%3Af8XECva7TN8nuPMDYjT9bM58v3smG0Owj4cRX9el31tFj5LeUYeS_wJcM5PB8Mqvd7zn1BG6NXE

Souza, R. B., & Powers, C. M. (2009). Differences in hip kinematics, muscle strength, and muscle activation between subjects with and without patellofemoral pain. *The Journal of orthopaedic and sports physical therapy*, 39(1), 12–19. <https://doi.org/10.2519/jospt.2009.2885>

[Nakagawa, T. H., Moriya, E. T., Maciel, C. D., & Serrão, F. V. (2012). Trunk, pelvis, hip, and knee kinematics, hip strength, and gluteal muscle activation during a single-leg squat in males and females with and without patellofemoral pain syndrome. *The Journal of orthopaedic and sports physical therapy*, 42(6), 491–501. <https://doi.org/10.2519/jospt.2012.3987>