Body Movement Recognition System using Deep Learning: An Exploratory Study

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Abstract: This paper presents an exploratory work using Deep Convolutional Neural Networks (CNN) in the context of detecting correct human movements during sports exercises, in particular specific physical exercises with the capability to perform the "5 times Sit-to-Stand Test" following the guideline of the Delaware university which is used in several settings to evaluate older adults' functionality. It is used a supervised learning model implemented with an opensource approach for the detection of the human body position with the calculation aspect and angles of the limb movements (e.g. the angle of the knee) in order to recognize if the exercises were or not well executed. Results have shown that, under normal operating conditions, an accuracy in the exercises detection around 80% using the CNN Mobilenet architecture. We conclude that with the implementation of the Posenet algorithm using Tensorflow via ML5.js we achieved results of correct exercises accuracy between 53% and 79% for exercises involving the lower limbs and accuracy around 45% to the upper limbs. Due the promising results achieved, we intent in the future to extend the work with complementary approaches of human body pose estimation to improve the training strategy and different CNN network architectures to perform the recognition accuracy in the applicability context of correct execution exercises in elderly population physical activity scenarios.

1 INTRODUCTION

Human motion capture is used in a variety of industries for biomechanics studies. A particularly interesting application makes use of motion capture data to train deep neural networks on human motion during various activities in order to predict a human's intent of motion in real time as well as the correct execution of the activities (e.g. sports exercises) (Menolotto el al., 2020). On another hand recognition of body movement is something that has applicability to many real-world problems.

Due the success of the mathematical foundations and applicability during decades, in the last years Artificial Intelligence, Machine Learning and Deep Learning (Wang, 2016; Liu et al., 2020) approaches in computer vision domain have also gained popularity in pose estimation due to the power of convolutional networks in object recognition and classification in particular for human pose estimation (Chen et al., 2017; Shavit & Ferens, 2019; Chen et al., 2019; Safarzadeh et al., 2019).

Promising results have been achieved and through the exploration of Deep Convolutional Neural Networks (CNN) (Wang, 2016; Liu et al., 2020; Chen et al., 2017; Shavit & Ferens, 2019) it is possible to develop robust technological applications (web and mobile based) for motion detection, recognition of a particular movement, human fall, etc. (Safarzadeh et al., 2019).

The main goals of this work were: i) study and exploration of CNN algorithms and implementations for character recognition with the movements of the body of a person (e.g., simulating sport exercises) and ii) use of opensource CNN algorithms implementations to recognize exercises if were or not

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being well executed in particular the angle of the knee and the body limbs. The application context was centred in an intervention program, named GMOVE (Vila-Chã & Vaz, 2019) to promote physical activity of the elderly population. It was also used the guideline of the university of Delaware (Delaware, U., 2022) for the assessment functionality settings of the exercises.

2 RELATED WORK

Concerning the risk of falls in elderly, Chen et al. (2020) presented the OpenPose algorithm to identify points on the body in real time and to analyse three critical parameters to recognize the fall down behavior achieving a rate of 97% of success.

Chen et al. (2019) presented a comparison of different types of networks that is made using pose skeleton map in figures. They concluded that when mapping the human body, the network would have a greater success because there would be a greater interconnection between the different types of the body limbs. Using the Intersection over Union (IoU) metric which determines how many objects were detected correctly and how many false positives were generated they achieve an accuracy of 95,39% comparing with the models of the ENet (Lo et al., 2019) (94,13%) and EDANet (Ramirez et al., 2021) (95,25%).

Furthermore, Chen et al. (2017) uses an approach for the identification of biologically natural or unnatural poses trough the Posenet model. The authors obtained 94.5% accuracy percentage when the wrists were visible in the images and 70.7% when not and for the elbows 95.1% and 77.6% respectively.

Likewise, using pose estimation and Multi-Layer Perceptron classifiers, Safarzadeh et al. (2019) found results of accuracy and loss reached 92.5% and 0.3 respectively. Ramirez et al. (2019) when focus their study on the perception of when there were falls, they extracted the key points of the human body with the pose estimation network and fed a Multi-Layer Perceptron, in which they used with the Rectified Linear Unit (RELU) and sigmoid activation function.

Borkar et al. (2019) investigate the use of Posenet (Chen et al., 2017) to compare positions by angles. The authors states that through 17 key points it is possible the calculation of the angles, to predict whether the movement was well performed. Their approach compares the shoulder coordinates and the wrist coordinates of an arm to locate if the arm is inward, outward, upward or downward. Similarly, for the leg comparison the system uses hip angle and knee angle.

3 METHODS

3.1 Theorical Framework

This work used recent CNN approaches and implementations in the Artificial Intelligence and Machine Learning field specifically to classify human body parts and human body estimation poses using Posenet algorithm which is built based on the CNN Mobilenet (Chen et al., 2017; Chen et al., 2019; Safarzadeh et al., 2019; Chang et al., 2019; Wang et al., 2020; Cao et al., 2016; Ramirez et al., 2021; Chen et al., 2020; Borkar et al., 2019). It was also used programming code available on web repositories such as GitHub to maximize the project implementation (Posenet, M., 2022; Renotte, D., 2022; Gruselhaus, G., 2022; Oved, D., 2022; Mediapipe, 2022).

As basis this work followed the studies of Chen et al. (2019) to count the number of exercises repetitions and Borkar et al. (2019) to measure the angle between joints in the body limb movements of the exercises (figure 1).

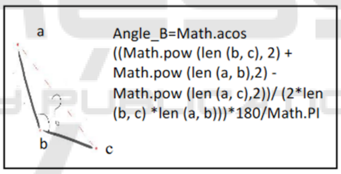


Figure 1: Formula for calculating the angle between joints (Borkar et al., 2019).

In practical terms it was created two prototypes with the implementation of Posenet. A web to allow the correct analysis of the character recognition with the movements of the body of a person (e.g., simulating sports exercises) and to recognize if the exercises were or not being well executed, particularly the angle of the limbs. The implementation was done using TensorFlow via ML5.js (Posenet, M., 2022; Gruselhaus, G., 2022; Oved, D. 2022). Additionally in order to provide an application to be used with mobile devices it was implemented a mobile app (android based) using Mediapipe framework (Mediapipe, 2022).

3.2 Application Context

The context of applicability of the work was centred in an intervention program, named as GMOVE (Vila-

Chã & Vaz, 2019) to promote physical activity and quality of life for the elderly population, following specific exercises and the capability to perform the "5 times Sit-to-Stand Test – *Five Times Sit to Stand*" as well as followed the university of Delaware guideline (Delaware, U. 2022) "Assesses functional lower extremity strength, transitional movements" in order to check the number of times a person can perform the exercises to stand up and sit in a chair for a certain amount of time.

The GMOVE manual is structured by 45 exercises to evaluate: cardiorespiratory resistance, muscle strength, balance and postural control and flexibility. To accomplish the research purpose, it was selected the exercises that accomplish: i) muscle strength exercises for the upper and lower limb; ii) exercises that do not require the use of exercise equipment's like rubber bands, dumbbells, etc.; and iii) performed with an isotonic contraction (Table 1).

Table 1: Exercises of the GMOVE Project (Vila-Chã & Vaz, 2019).

#	Category	Member Position	Objective	(*)
1	Muscle strength	Lower limbs	Sit to Stand on the chair	X
2			Squat with weight	
3			Isometric sitting position against the wall	
4			Hip extension	X
5			Dead lift with support	X
6			Lateral leg lift	X
7			Shoulder bridge	
8			Knee flexion	X
9			Seated knee extension	X
10			Standing plantar flexion in the ground	X
11			Standing plantar flexion in a step	
12			Seated Plantar flexion	X
13	Muscle strength	Trunk - back	Row with elastic	
14			Shoulder horizontal extension with elastic	
15	Muscle strength	Trunk - Pectoral	Push-up on the wall	X
16			Dumbbell's chest press	
17	Muscle strength	Shoulders	Seated military shoulder press	
18			Front raise with dumbbells elevation of arms	
19			Seated shoulder lateral rise with dumbbells	
20			High row	
21	Muscle strength	Upper limbs	Biceps curl with dumbbells	
22			Kick back with dumbbells	
23			Tennis ball hand squeeze	
24			Towel twist	X
25	Muscle strength	Core muscles	Sit ups	
26			Sit up with heels t	
27			Diaphragmatic breathing	
28			Alternate extension of arms and legs (dead bug)	
29			Bird Dog exercise	
30	Balance and flexibility	Balance	Single leg stance	
31			Toes rises and heel stance	
32			Inline walking	
33			On leg stance walking	
34	Balance and flexibility	Flexibility	Neck stretch	
35			Shoulders internal and external rotation	
36			Back scratch with a towel stretch	
37			Fists stretch	
38			Shoulder horizontal flexion and extension	
39			Trunk mobility stretch	
40			Scapular stretches	
41			Lower back stretch	
42			Quadriceps stretch	
43			Hamstring stretch	
44			Calf stretch	
45			Ankle dorsiflexion and plantarflexion mobilization	

In parallel following the “5 times Sit-to-Stand Test” protocol by checking the number of times that a person can perform for a certain amount of time, that assesses functional lower extremity strength, transitional movements, balance, and fall risk, with cut off points and reference values for several populations it was intent to evaluate older adults’ functionality (Marques et al., 2014).

3.3 Procedures

Individually, two human models, proficient in the execution of the motor tasks were used to perform the exercises. According to the inclusion criteria it was implemented 10 of the initial 45 exercises (Table 1). Following the related work presented in the previous sections and in order to implement the prototype for identification and classification of human body parts for contactless screening systems it was created a principle to adopt after the gathering the images from the exercises (figure 2).

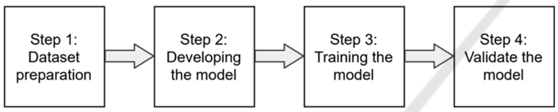


Figure 2: Principle adopted after collecting images with Posenet and ML5.js.

In the first phase, it was managed to prepare the dataset to test the data in the latter phase. Next, was started the development of the model to identify and classify body parts, more specifically the chest area, evaluating the pictures taken in the previous phase. Lastly, was implemented the methods from the previous point to create the practical applications (prototypes) to recognize the exercises and if were well executed.

3.4 Architecture

In the first phase (figure 3), it was managed to prepare the dataset to test the data in the latter phase. Next, was started the development of the model to identify and classify body parts, more specifically the chest area, evaluating the pictures taken in the previous phase. As mentioned after it was implemented the methods from the previous point to create the prototypes and use the models.

The process followed three steps: i) Creating the Model: it was created a local server to run all the services to develop the first model; when the page starts, the user has to accept permission to access the camera and is able to create the first model. As soon as the data collection is finished, the process can be repeated or finished; ii) Training the Model: to be able to train the model, a previously saved file must be placed inside the training folder and changed the name of the parameter to the respective name of the saved file. The first model was trained and saved three files, which will be the training models (dataset models), named "model", "model weights" and "model meta; iii) Testing the Model: if all the previous steps were successfully completed was possible to test the created models.

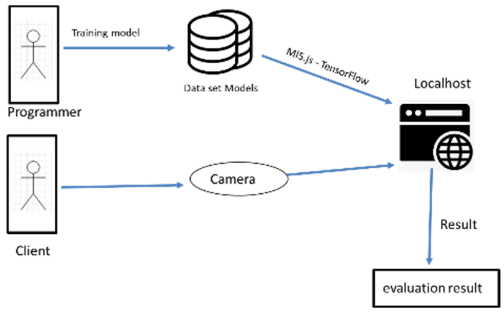


Figure 3: General Architecture.

In the web prototype the client put the computer in front then, execute the squat and the localhost save the exercise in video. With the view of the angles, he can recognize if is being performed according to the norm and thus increase the number of repetitions done (figure 4 – (a) – computer/web based and figure 4- (b) – mobile app - android based).

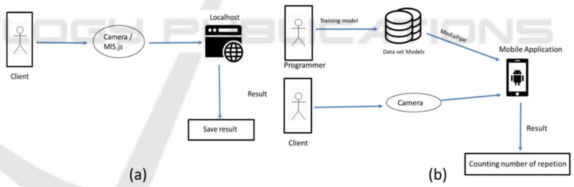


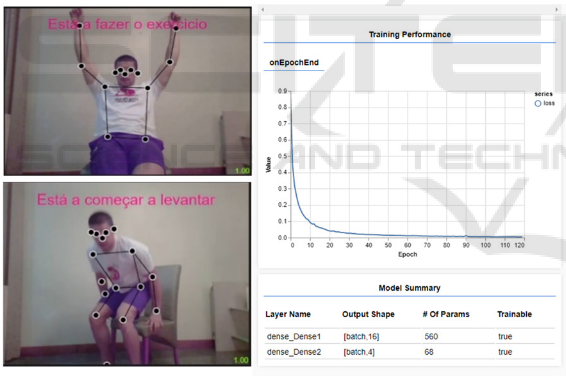
Figure 4: General Second Architecture (a – web based; b – Android Based).

Following the same approach as the architecture of the web platform, which allows to check whether an exercise was well performed or not, in the mobile application it was added the functionality of counting the number of repetitions executed. The mobile version differs from the web in not allowing the visualization of metrics in the creation of the models since was using Mediapipe which does not currently provide this information. For this reason, the process of creating models using Posenet (web platform) allows the analysis of the models performance while using Mediapipe (mobile application) does not allow to assess the performance of models against the data set. Throughout, the images to train this model via the Mediapipe followed a different approach, with an image of the exercises in a start point (input) and another in the end of the exercise (output) with the human body estimation. These images must have very high resolution (best possible quality) and submitted to Mediapipe and the model is created.

3.5 Dataset and Data Processing

When using ML5.js to train the model and get the dataset it was necessary to record a video in each exercise phase, with a resolution of 640x480, obtained directly from the computer web cam. Considering the 10 included exercises, it was necessary to validate the number of situations that each exercise include and record a video for each stage. The measures of the joint angles, especially the flexion and extension on the knee, were visual inspected and assessed with an accelerometer-based smartphone application.

The dataset consists of 20 videos, with no image processing. It was developed a web platform for the recognition of exercises using ML5.js with Posenet and a mobile prototype using the Mediapipe. For each exercise it was trained with the specific video as presenting in the figure 5.



(a) (b)

Figure 5: Example of the model training (a) (ex for the exercise "*is starting to lift*" or "*está a começar a levantar*" *(in portuguese language)* and model performance for the exercise 1 (b).

On the web platform, which allow to verify the correct execution of an exercise by calculating the angle of the joint by using the formulas from the work of Borkar et al. (2019). It was necessary to add more information such as age and gender to match the use of the sit to stand test metrics. Due to this fact, in the process, a form was made available to associate the video to these characteristics in order to be able to use the formulas in alignment with the guidelines of the "5 times Sit-to-Stand Test".

To create the model, after filling out the initial form, it was needed to perform the exercise as many times as possible, following the previously defined procedures.

After completing the exercise, the video was downloaded and created the title, name, age and number of repetitions according to the previous guidelines (Delaware, U., 2020).

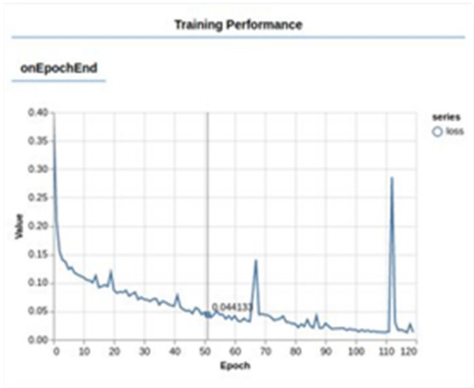
3.6 Model Training and Validation

Posenet approach and implementations (Chen et al., 2017) with Tensorflow via ML5.js (Posenet, 2022; Gruselhaus, G., 2022) were used for the web platform and Mediapipe (Mediapipe, 2022) for the mobile app. The dataset, data processing section and the models creation followed different approaches. The wed platform used video to create the models and the other used initial and final images of each exercise. In the models created on the web platform, depending on the exercise model, the results were different. The models were trained with a computational environment using a CPU with an Intel Core i7-7700HQ processor (2.8 GHz), 32GD DDR4-2400 RAM, NVidia GForce GTX 1060 of GPU, HDD (1Tera) and SSD 462GB and a HP Wide Vision WebCam (FHD IR Camera).

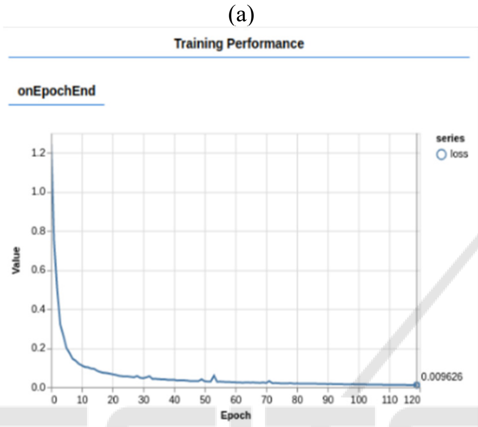
According to several values of epochs, for the tested exercises, it was found the least loss by 120 (figure 6 (b). It should be noted that this being a proof-of-concept work, it was also conducted a training with 500 epochs. However, the computational power was too long, and in practice no results were seen much better. After each workout, was performed the exercise in live mode to analyse the performance results. In the "5 times Sit-to-Stand Test" we used the calculation of knee angles to check when the person gets up from the chair, thus counting the number of repetitions according to the calculation method described in Chen et al (2019).

Typically in CNN evaluation are used some specific metrics (Liu, 2020; Shavit & Ferens, 2019; Ramirez et al., 2021) based on false positives, false negatives, true positives, true negatives as the confusion matrix, model accuracy, precision, root mean square error, f1-score as well as some CPU and GPU performance processing metrics, as the average of the Average Precision (mAP) and the Intersection over Union (IoU) metric determines how many objects were detected correctly and how many false positives were generated.

The models were trained and evaluated with the detection accuracy and loss of the output camera pose estimated by the DSAC - differentiable ransac (Random Sample Consensus) for camera localization (Brachmann, 2017).



(a)



(b)

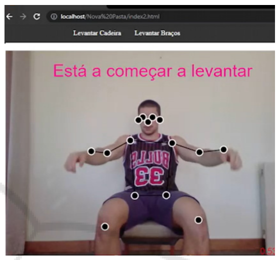
Figure 6: Training chart with 120 Epoch.

The evaluation of the models for the web prototype using Posenet with Tensorflow via ML5.js are presented in figure 6 (a; b) for 70 Epochs and 120 Epochs respectively. More than 120 Epochs the results are similar to the 120 Epochs.

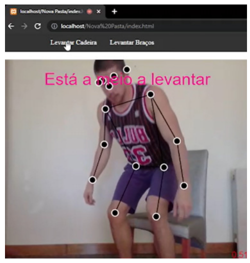
The model creation procedure in the mobile prototype differentiated a few from the web prototype described above. The Mediapipe version used to create the models in mobile app not allowed to provide detailed statistics of the models created and in the recognition user step only provides the general accuracy of the exercise. Consequently, the images to train this model via the Mediapipe have to follow a different approach, with an initial image and a final image of the exercise with the best possible image quality. In this sense with Mediapipe the models were created but the performance metrics were unknown. However, using the mobile app we consider that the performance is high due the results of the exercises recognition accuracy in general was high (around 99% in the simulations). In this sense, in the results and discussion section we will focus only on the models and exercises recognition performance provided by the web prototype and only in the exercises recognition performance using the mobile app.

4 RESULTS AND DISCUSSION

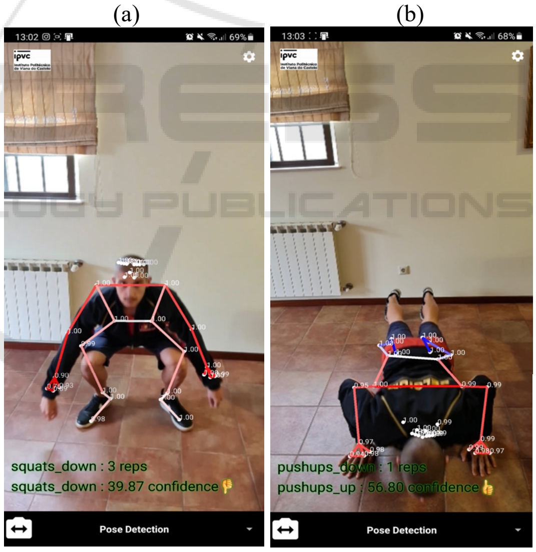
The model's performance from the prototypes were quite promising considering the tests performed in the exercise's recognition. Figure 7 illustrates an example of the exercise recognition in the two prototypes and correct validation of the exercises. For example in the mobile app (figure 7 (c)) a hand icon in the caption in the end of the app form and colour green or red if the exercise is well or not well executed. In the web it is presented a message.



(a)



(b)



(c)

Figure 7: Examples of the web platform (a) "raise arms" and (b) "bicep exercise done correctly" and mobile app (c) correct (or not) exercise's recognition simulation.

As we mentioned in section 3.6 due the limitation to access to the detailed model creation performance metrics provided by Mediapipe and the general accuracy provided in exercises recognition in the mobile app it was only presented in the app form the general recognition accuracy. However, we programmatically complemented this lack with the

Table 2: Loss value, accuracy and results for the ten exercises performed and trained.

	Exercise	Loss	Accuracy	Results
1	Sit to Stand on the chair	0.042	0.787	Promising results#
4	Hip extension	0.030	bad recognition *	Did not get results
5	Dead lift with support	0.021	0.787	Promising results with low reliability
6	Lateral leg lift	0.120	0.537	Promising results#
8	Knee flexion	0.055	0.612	Promising results with low reliability
9	Seated knee extension	0.150	bad recognition *	Low reliability
10	Standing plantar flexion in the ground	0.010	0.474	Low reliability
12	Seated Plantar flexion	0.130	0.180	Low reliability
15	Push-up on the wall	0.200	0.458	Promising results with low reliability#
24	Towel twist	0.012	bad recognition *	Did not get results

* - bad recognition; # - low reliability; Loss – represents a minimizing score (loss)

calculation aspect of the angles of the limbs, using the formulas of Borkar et al. (2019) in the exercises in order to verify if were well or not executed as well as counting the number of repetitions executed following the university of Delaware guideline (Delaware, U., 2022) for the assessment functionality settings of the exercises.

On another hand, some of the models created were not able to recognize the exercises. One reason was the operational conditions of the video capture (in the creation of the models and in the exercises, recognition using the models) and the environment scenario background around the person, luminosity, objects, etc. being the normal conditions a scenario without any objects (or a few) behind the person during the exercises or with a white wall in the background scenario or the "ideal" conditions a scenario without any objects and a white "wall" in the background, for example.

Another reason is due the little variation in the exercise movements, making impossible to detect changes during the exercise. For example, the fact that exercises being in a lateral plane made it difficult to locate the key points of the body and thus confused their identification, as only part of the key points of the body were moved. Table 2 presents the results for the performance of the ten exercises tested and trained.

For some exercises we have a bad recognition or low reliability, identified with the characters '*' and "#" in table 2. For the exercise 5 was achieve an accuracy of 79%, exercise 15 an accuracy of 46%. In the exercise 24, it was evidenced that this exercise had a bad accuracy. The good results for the lower limbs were achieved particularly in exercises with strong movements, namely, for the exercise 1 with an accuracy of 79%, exercise 6 with 53%, exercise 8 with 61% and exercise 10 with 47%. The exercise 12 presented a low accuracy and exercise 4 and 9 had a bad recognition.

To evaluate the robustness of the Posenet model, real images without "ideal" conditions from outside our dataset have also been used. Moreover, a conventional webcam has also been used to evaluate in a live stream the quality of the obtained data. In terms of model accuracy and model loss. The *Loss* and the *Accuracy* represent the evaluation on the training and validation data which gives an idea of how well the model was learning and generalizing (Table 2). The model loss represents a minimizing score (Loss), which means that a lower score results in better model performance. The model accuracy represents a maximizing score (*Accuracy*), which means that a higher score denotes better performance of the model in the recognition.

We consider that the results were promising in terms of performance in the web prototype with a recognition accuracy of the exercises around 80%. The bad recognition or low reliability can be also intermediated by the fact of the exercise's particularities and the relation of the camera and model detection of the exercise's movements.

In the exercise 24, it was evidenced that this exercise had a bad accuracy because the key points never change position, or the changes weren´t significative due the fact of the low movements detected by the camera in the wrist level.

In our exploratory work, it was possible to denote that the more variation in the different points of the body greater is the percentage of success in predicting the movement, independent of being web based or mobile app. It was also possible to observe that there were some human movements that demonstrate bad recognition. These low or poor recognition, in particular exercises 4, 9, 12, 24, were mediated to the specificity of each exercise in the process of collecting the videos, which in the future should be given more attention in the recording phase. For example, if an exercise does not change the positioning of the key points, the model cannot check whether the exercise has been performed. These key points of the upper body where the eyes, ears, right and left shoulder, elbows, and wrists. In the lower body the key point was the right and left side of the hip, the knees, and the ankle.

From another point of view and execution if the exercise was being performed in a lateral plane, or if the person had some part of the body hided, the model cannot measure whether the exercise was being performed, because only part of the key points of the body were moved. For the lower limbs the results were more sensible, particularly exercises if there were significant joint movements, namely, for the exercise 1, 6, 8 and 10. Nevertheless, exercise 12 presented a low accuracy possibly because being observed in the lateral plane and only the ankle had a significant movement with the hip and knees key points do not change significatively.

The exercise 4 and 9 had a bad recognition possibly because also being observed in the lateral plane and difficult to recognize the body movement by the camera and consequently by the model. Though, the lateral plane observation/record of the exercise must be looked with caution and mostly concerning reliability since exercise 5, 8 and 12 demonstrate promising results with low reliability and were tested in the lateral plane.

The human movement is inherently complex, dynamic, multidimensional, and highly non-linear requiring to work in predictive modelling, classification and dimensionality reduction (Zago et al., 2021). However, these results may also being mediated by the number of observations since the data set is also a key factor and when the number of observations in a dataset is smaller than the number of features the feature space is reduced (Halilaj et al., 2018).

On another hand, when exploring the angles in which it is possible to associate a movement it was found that the best results were only generated when changing the angle of 3 key points, which can serve as a complement to exercises that are more difficult to create prediction models and in the future it will be interested to explore different plus functionalities for measuring the angle of the arms and legs movements as well as with different physical statures of the persons during the execution of the exercise movements in order to evaluate the discrepancy of the body limbs length if influences or not the recognition accuracy using the CNN approaches.

5 CONCLUSIONS

This work merges the potentialities of the Artificial Intelligence techniques in the field of computer vision, using Convolutional Neural Networks (CNN) applied in the context of human movements in particular for physical exercises of elderly persons following an intervention program to promote their physical activity with specific exercises as well as a guideline to evaluate older adults' functionality.

Using opensource CNN algorithm implementations the aim was to recognize if the exercises movements were or not being well executed in particular the angle of the skeleton limbs. Using the camera devices two prototypes have been created: a computer web based and a mobile app. The web uses the Posenet algorithm which is based on the CNN Mobilenet approach for movements recognition and was implemented using Javascript with TensorFlow via ML5.js. We achieved correct exercises accuracy between 53% and 79% for exercises involving the lower limbs and accuracy around 45% to the upper limbs.

The mobile app using Posenet was implemented via Mediapipe framework and in order to detect the position of the human body and verify if the exercises was performed correctly the app was complemented with the calculation aspect of the angles of the limbs. However, due the specificity of the actual version of the Mediapipe in not allowing to view and analyze the model's performance as well as the detailed statistics in the recognition, only presenting the general accuracy, we assume in this prototype that the creation of the models achieved high rates and accept the values of the performance rate provided by the framework (around 99% in the simulations). In this sense both prototypes were used for the exercise recognition and correct execution but only was analyzed the model's performance created in the web prototype.

We consider due the promising results achieved in the future will be interesting to extend the work with complementary approaches of human body pose estimation to improve the training strategy and different CNN architectures in the applicability context of physical exercises for elderly population as well as in a higher scale of persons and scenarios.

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