Predict The Caloric Expenditure and Pose Estimation Through the Assistance of The Virtual Gym Coach

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Abstract— This research paper introduces a novel virtual gym assistant leveraging Google's Mediapipe library, designed for diverse multimodal machine learning and deep learning pipelines. The system offers real-time guidance by analyzing user movements during specific exercises using posture estimation algorithms. Developed with Mediapipe's deep algorithms and pose estimation module, the system captures user movements through the identification of body landmarks, facilitating rep counting for each exercise. Angles and landmarks are then processed and transmitted to various machine learning models, enabling the classification of correct postures and reps. Through machine learning algorithms, the system evaluates the accuracy of user-performed reps. Utilizing diverse fitness datasets and custom data, the results demonstrate that the proposed system delivers precise and personalized feedback, enhancing exercise performance and minimizing the risk of injury. Additionally, the system calculates caloric expenditure, providing comprehensive support for users through the Virtual Gym Coach

Indexterms— Calories Expenditure, Mediapipe, Computer Vision,, Workout, Exercises, Deep Learning

1. INTRODUCTION

Engaging in physical activity has become essential in today's world, contributing to the strengthening of bones and muscles while enhancing overall functional abilities. With a growing awareness of fitness and health, individuals dedicate time to daily exercise routines, whether at home or in the gym. The COVID-19 pandemic prompted a surge in home workouts, driven by health-conscious individuals looking to maintain their well-being in the absence of gym access. However, this shift to home-based exercise presents challenges, as individuals may lack knowledge of proper exercise posture, leading to potential injuries and complications. Given the current trend of exorbitant gym prices, many people prefer the convenience of home workouts.

This project introduces a unique approach to home exercise, eliminating the need for daily gym visits. Leveraging Google's Mediapipe library, we detect human body landmarks, including shoulders, elbows, knees, wrists, ankles, etc., and utilize this information to calculate the number of completed reps. This document specifically outlines a rep counting system for popular exercises such as bicep curls, squats, planks, front kicks, and jabs.

Biomechanics plays a crucial role in our approach as we focus on estimating the correct posture for each exercise. Furthermore, we employ machine learning and deep learning models to assess pose accuracy and the correctness of exercise form. The document explores the comparison of accuracy across different machine-learning techniques, including variations with and without hyperparameter tuning, using a custom dataset. Additionally, a deep learning approach is employed, utilizing an Artificial Neural Network (ANN) to calculate accuracy. The collective comparison of these techniques aims to identify the most suitable approach for the project.

In addition to these advancements, we extend the functionality of our system by incorporating the capability to calculate caloric expenditure. Through the assistance of the Virtual Gym Coach, users can now receive comprehensive support, ensuring not only the accuracy of their exercises but also providing insights into the energy expended during their home workouts.

2. LITERATURE SURVEY

In the realm of pose estimation, an array of research endeavors employing the Mediapipe library has emerged. Halder et al. conducted a comprehensive study comparing machine learning models, such as SVM and KNN, for sign language detection in American, Indian, and Italian languages. Their methodology incorporated the Palm Detection Model of Mediapipe, focusing on hand images. A multi-step architecture was proposed, involving landmark extraction, cleaning, normalization, and training/testing data splitting. SVM demonstrated superior performance among the evaluated algorithms [3]. Singh et al. delved into the challenges of pose estimation, presenting a straightforward model utilizing a convolutional neural network (CNN) to estimate postures, showcasing the potential of CNNs after extensive examination [11].

Several works specifically address gym exercises and yoga poses. Chen et al. implemented a gym exercises assistant model using geometric heuristics and a machine learning strategy, incorporating the OpenPose model for post-estimation with part affinity fields [2]. Agarwal et al. explored AI applications in the fitness sector, suggesting machine learning for asana correctness assessment. They utilized the BlazePose model for pose detection and implemented a heuristic approach for angle calculation between landmarks [5]. Li et al. proposed a methodology for classifying basic fitness movements using Mediapipe, emphasizing the suitability of the Blazepose model for personalized AI fitness on mobile devices [8]. Kumar et al. developed an Android application for yoga pose estimation utilizing the OpenPose model, comparing real-time poses with preprocessed local machine data [14].

Another approach introduced by Taware et al. involved occlusion-simulating augmentation to assess posture detector performance in challenging scenarios. Their estimator determined user positions before employing both regression and heatmap methods in the training model [9]. Kanase et al. described a pose estimation methodology using the OpenPose model, incorporating heuristic and machine learning approaches based on dynamic time warping [13]. Anilkumar et al. utilized the BlazePose model to acquire body joint coordinates, allowing users to set flexibility thresholds for personalized feedback on yoga positions [15]. Additionally, others adopted a similar approach for AI-fitness repetition capabilities, using BlazePose for landmark coordinates and geometric heuristics for exercise angle assessment [16]

3. PROPOSED METHODOLOGY

The complete process pipeline is separated into two stages which are described below:

3.1. Landmark Detection Stage

The participant is instructed to position themselves in front of the camera, ensuring that the camera captures the regions of interest clearly. Leveraging the capabilities of Mediapipe, the initial step involves detecting the subject or the designated region of interest (ROI) [1]. Employing Mediapipe's advanced Pose Landmark Model, we proceed to identify and capture the specific landmarks corresponding to various body parts, a topic that will be elaborated upon later in the discussion

3.2. Rep Counting Stage

i. In the initial step, we gather all landmarks from a specific frame and proceed to compute the angles formed between the designated reference landmarks. These angles are then subjected to a threshold function based on angle heuristics, with unique thresholds assigned to each exercise. If the angle extracted meets the specified threshold, we increment the rep count by 1; otherwise, it is incremented by 0.

ii. Upon satisfying the angle threshold criteria, the extracted landmarks are inputted into a machine learning model designed to classify the pose's form, providing insights into the accuracy of the exercise execution. If the confidence score for the correct form surpasses 60 percent, the current repetition is validated, and the rep count is incremented accordingly. Conversely, if the confidence score falls below this threshold, the rep count is incremented by 0, and the assessment continues. To enhance accuracy in determining the correct pose, we have implemented and compared various machine learning (ML) and deep learning (DL) models for form classification, seeking optimal results.

3.3. Calculation of Calories Expenditure

In the intricate dance of caloric expenditure, our bodies reveal a profound connection between physical activity, metabolism, and overall health. By unraveling the complexities of BMR, physical activity, muscle mass, and other contributing factors, individuals can make informed choices to optimize their caloric balance. Empowered with knowledge, we can embark on a journey towards a healthier, more active lifestyle, mindful of the intricate interplay that determines our daily caloric expenditure.

In this table calories expenditure details are mentioned.

S.NO	Exercise Name	Calories burn per rep
1	Biceps Curl	0.375
2	Squats	0.32
3	Bench Press	0.147
4	Front Kick	0.235

3.4. ALGORITHM SUMMARY

3.4.1. Pose Detection and Angle calculation

Pose detection makes it easier to keep track of the posture during any exercise set. Pose detection models have a set of predefined landmarks which help in identifying various body parts easily.

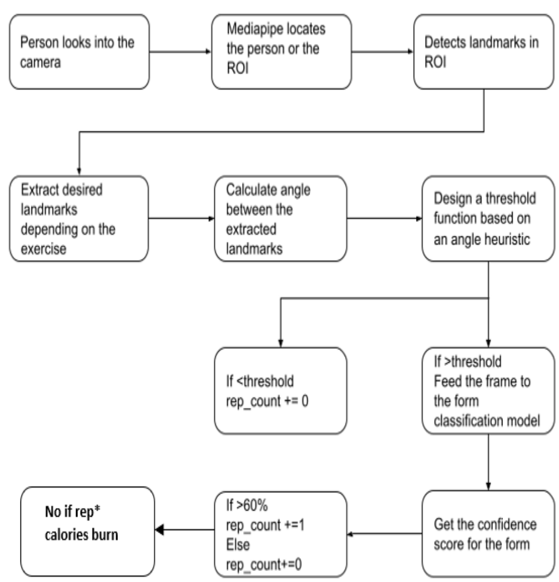

Fig. 1: Process Pipeline

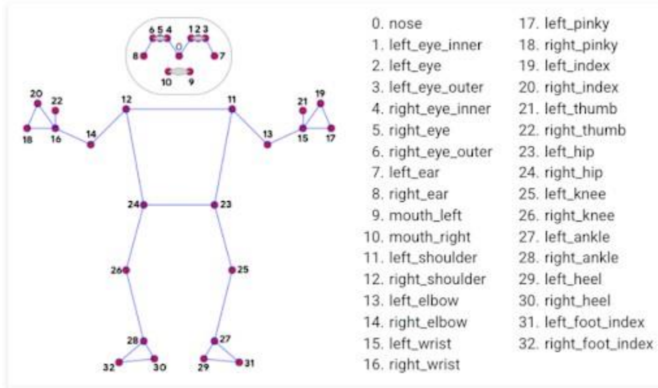

Fig. 2: Landmarks of Mediapipe's Blaze Pose Model [1]

Some examples of pose detection models include PoseNet, AlphaPose, OpenPose, and many others. After some research, BlazePose was the model selected for this application.

1. *The BlazePose Model:* Mediapipe's pose detection API implements the BlazePose model. The BlazePose model per- forms slightly worse compared to the OpenPose model, but it is an ideal choice for Yoga/Fitness poses. The proposed systemuses the Pose Detection API for landmark detection. Figure3 below depicts the landmark coordinates from BlazePose's pose and landmark detector model which provides human pose tracking. It is a human pose estimation model developed by Google Research that can detect 33 key points of the human body, including the head, torso, arms, and legs. BlazePoseis designed to be fast and accurate, making it well-suited for real-time applications such as fitness tracking, virtual try- on, and gaming.BlazePose is based on a lightweight neural network architecture that uses a combination of convolutional and depthwise separable convolutional layers to achieve high accuracy while minimizing computational complexity. Themodel is trained on a large dataset of annotated images and uses a combination of supervised and self-supervised learning to improve its accuracy over time. We will extract desired landmarks for calculating specific angles which are required for particular exercises and then predict the accuracy and countthe number of reps [1].

2. *Algorithm used for detecting Squats:* Squat analysis can be performed by dividing motion into three complete domains.Upper body, lower body, and movement mechanics. The lowerbody evaluates the alignment of the hip, knee, and ankle landmarks, the upper body focuses on stability and posture of the head, neck, and stomach core, and movement mechanics evaluate workout time and coordination. The shoulder, knee, hip, ankle, and foot joints and their spatial angles are used for posture or attitude calculation. The hip angle is calculated by the back and the thigh landmarks. The knee angle is calculatedby the thigh and the lower leg landmarks. The landmark coordinates are extracted from BlazePose's pose and landmarkdetector model which provides human pose tracking of 33 landmarks [1] [2]. Given below is the heuristic value of the various angles used to check for a correct and accurate squat posture.

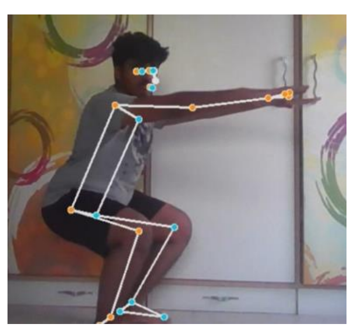

Fig. 3: Squats exercise implementation

TABLE I: Table of Threshold heuristic angle values for Squatsexercise

Angles	Heuristic Values	Remarks
Hip Angle	50-71 degrees	less than 44 degrees will cause imbalance
Knee Angle	55-68 degrees	greater than 75 degrees will reduce the effect of the rep
Torso Angle	35-43 degrees	greater than 45 will lead to incorrect posture
Ankle Angle	75-85 degrees	less than 75 will cause too much strain on the ankles

3. *Algorithm used for detecting Bicep curls:* There are two heuristics that are of utmost importance while calculating the bicep angle pose correctly [4]. When the angle between the upper arm and torso is greater than 30 degrees, it results in an incorrect curl because the upper arm is being rotated too much. This excessive rotation of the upper arm is usuallybecause of lifting heavy weights which the body cannot tolerate enough[11].

Initially, the angle between the forearm and the upper arm would be 150-180 degrees. This angle decreases when the forearm goes all the way up and the bicep muscles contractand increases when it goes back to its initial position and the muscles relax. If the angle between the upper arm and the forearm is greater than 70 degrees during contraction, the curl is improper, and thus by using these measures and threshold values we count the number of reps and predict the accuracy accordingly [4]. So we use the shoulder, hip, elbow, and wrist joints for the bicep curl pose estimation.

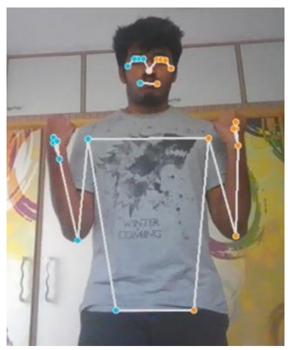

Fig. 4: Bicep curls exercise implementation-1 (Closed arms)

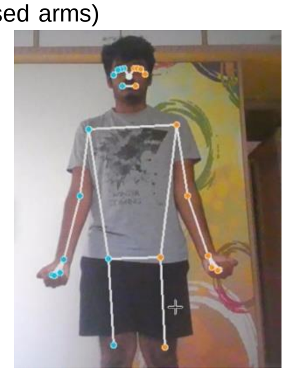

Fig. 5: Bicep curls exercise implementation-2 (Open arms)

TABLE II: Table of Threshold heuristic angle values for bicepcurls exercise

Angles	Heuristic Values	Remarks
formed by torso and upper arm	less than 35 degrees	greater than 45 degrees will resultin incorrect rep
Formed by upper arm and forearm during contractionof bicep	less than 70 degrees	greater than 70 degrees meansincomplete rep

4. Algorithm used for detecting Boxing-jabs: We will be looking at two main heuristics in the jab punch exercise as well. To invigorate your punch, we just need to have a the hip, shoulder, elbow, and wrist joints of both arms for calculating reps. The first angle to be calculated will be generated using the shoulder, elbow, and wrist joints. Thesecond angle, which is more important in jab punching is the angle formed between the hip, shoulder, and elbow joints [10]. Let's refer to the angle created by the wrist, shoulder,and elbow as the arm angle and the hip, shoulder, and elbowas the hip-rotate angle. Let's refer to the angle created bythe wrist, shoulder, and elbow as the arm angle and the hip, shoulder, and elbow as the hip-rotate angle. Let us also consider 2 stages while throwing a jab – in and out stage.

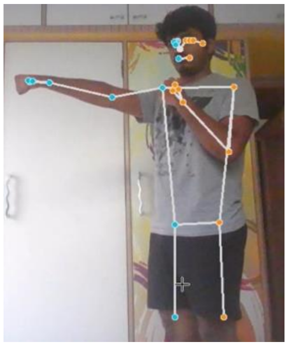

Fig. 6: Boxing- Jab Punch exercise implementation

The 'in' stage signifies that the arm is resting and the arm angle and hip rotation angle are about 15 degrees. Thisis also the initial state before the user starts this exercise. The 'out' stage signifies that the arm is stretched out to throwa punch and therefore the arm angle should be greater than150 degrees. For a perfect, invigorating punch the hip and shoulder should be utilized correctly. If the hip-rotate angleis between 80-100 degrees, it is an almost ideal punch asmost force is generated in this angle range. Thus looking atthe hip rotation angle we calculate the number of reps in this workout.

TABLE III: Table of Threshold heuristic angle values forBoxing- Jab Punch exercise

Angles	Heuristic Values	Remarks
Arm Angle(shoulder-elbow-wrist)	150-180 degrees	less than 140 will generate lesser force
Hip-Rotate Angle(hip-shoulder-elbow)	80-100 degrees	less than 65 degrees will work the armsmore

5. *Algorithm used for detecting Front Kicks:* Similar to some of the above exercises we will be focusing on two heuristic angles for this as well. The joints we will be usingare the ankle, knee, hip, and shoulder. The angles we will be looking out for are the one formed between the ankle, knee, good amount of hip rotation so that the entire weight of the upper body is transferred in the punch itself, therefore, generating enormous power. Furthermore, our arms shouldnot be bent while throwing a punch. So we will be using and hip joints(leg angle) and the other formed between the shoulder, hip, and knee(hip angle). Let us consider 2 stages while performing one rep of a front kick – the in and outstage. The 'in' stage is the initial stage and the 'out' stage is the stage where the kick takes place and one of the legs movesaway from the body. During the 'in' stage, leg and hip angles should be fewer than 50 degrees and 70 degrees, respectively. The table given below shows the heuristic values for a correct front kick during the 'out' stage.

TABLE IV: Table of Threshold heuristic angle values for FrontKicks exercise

Angles	Heuristic Values	Remarks
Leg angle(hip-knee-ankle)	more than 120 degrees	less than 110 degrees will resultin incorrect posture
Hip angle(shoulder-hip-knee)	71-120 degrees	more than 130 degrees will workthe back muscles more

3.5. Form Classification

Although the angle heuristic might be satisfied in somecases, it is not extremely reliable and hence it is also necessaryto keep a check on the form of the subject while they perform each rep. Thus, if the threshold condition triggers, we testthe form of the subject at that point by passing the current landmarks to a model trained on the acceptable postures forthe exercise at the standard points of a rep count.

If the model classifies the current form into one of the valid posture labels with a confidence score of a minimum of 0.6, we validate the rep and increment the rep counter otherwise skip it. For this further experimentation, we have focused on only one of the exercises – bicep curls. Different models were trained on the images of people performing bicep curls while at the endpoints of a rep - an open arm position (labeled ‘1’) and a closed arm position (labeled ‘0’).

1. *Machine Learning Approach:* We used four different machine learning models for our research viz. Support Vector Machine, Logistic Regression, Naive Bayes Classifier, and Decision Tree Classifier. These classification models wereused to compare the results and to find out the best classifier for our dataset. We used these models with and without hyperparameter tuning to understand the changes in results after performing the latter and to ensure more efficiency in classification.

2. *Deep Learning Approach:* For the deep learning ap-proach, an Artificial neural network (ANN) was used. In the ANN model, there are several dense layers of a number of neurons. The model has a 32-neuron input layer followed bya 16-neuron hidden layer and a single neuron output layer.The first and second layers have a ReLU activation function while the last layer has a sigmoidal activation function. Our model uses binary cross entropy as the loss function. It was also observed that using more than 3 layers causes the networkto overfit.

4. DATASET

A Custom Dataset is required for our machine-learning approach for the pose detection of exercises. The main focusis on the bicep curls and squat exercises. For this purpose, we generated a dataset using another dataset on Kaggle uploaded by Jiunn [6]. The dataset consists of 3 different exercises, out of which we only utilized the data for bicep curls. The datais present in the form of short videos whereas we require image data of the correct pose. Therefore, data extraction was performed on the Kaggle dataset to obtain images from the videos. The frames were selected when the angle heuristic threshold condition was satisfied.

Another dataset uploaded by Abdillah on Kaggle [7], wasalso used for data generation. The images were manually filtered to get the most suitable images for our use accordingto the criterion mentioned previously. Even after filtering out numerous images and videos, the dataset was still short. Therefore, there was a need to create more images and forthe same purpose, we introduced some of our own pics inthe required pose. The Pose Landmark Model of Mediapipe was used on these images to obtain the landmarks of the pose which need to be detected. These landmarks were saved in a CSV file format as the final dataset.

5. IMPLEMENTATION

After employing the default parameters for the four machine learning models, we proceeded to fine-tune the hyperparameters using GridSearchCV, aiming to identify the optimal settings as outlined in Table 5. GridSearchCV not only assists in hyperparameter tuning but also facilitates cross-validation, with the number of folds set to 5 for each model.

In the case of the deep learning approach employing an Artificial Neural Network, we extended the tuning process using the GridSearchCV algorithm. This encompassed exploration of different configurations for layers, batch sizes, activation functions, and epochs. The objective is to enhance the model's performance in accurately predicting calorie burn during exercise.

The comprehensive tuning process, incorporating both traditional machine learning models and a deep learning approach, ensures that our models are fine-tuned to the specific nuances of the data. Once the models are optimized, we can leverage them to predict calorie burn based on the repetitions of each exercise, providing a more accurate estimation of energy expenditure during physical activity.

6. RESULTS

Our study utilized advanced machine learning techniques, including Support Vector Machines (SVMs) and Logistic Regression with hyperparameter tuning, for accurate posture assessment during various exercises. Leveraging the MediaPipe library's pose estimator model, we determined the correct reps using heuristic functions and set thresholds. Our chosen machine learning pipeline, Logistic Regression with hyperparameter tuning, yielded the best results in predicting exercise states and estimating calories burned during each workout. This approach provides a robust and efficient method for assessing physical activity intensity

TABLE V: Hyperparameter tuning

Models	Hyperparameters Tuned
Support Vector Machine	- Regularization parameter(inverse) -'c' - Kernel coefficient for 'rbf','poly' and 'sigmoid'- gamma - Kernel type – kernel
Logistic Regression	- Regularization strength -'c' - Kernel Penalty i.e.L1/L2/both - Kernel Algorithm to use in the optimization problem – solver
Naive Bayes Classifier	- the proportion of the max- imum variance of all fea- tures that is included in the variance calculation - 'var smoothing'
Decision Tree Classifier	- criterion - max leaf nodes - min samples split - min samples leaf - max depth
Artificial Neural Network	- layers - batch sizes - activation functions - epochs

TABLE VI: Table of accuracies of ML models

Sr. No.	Model	Train samples	Test samples	Accuracy
1	Support Vector Classifier	137	60	98
2	Logistic Regres-sion	137	60	98
3	Na¨ıve Bayes Classifier	137	60	77
4	Decision Tree Classifier	137	60	97

TABLE VII: Accuracy overview of tuned ML models

Sr. No.	Model	CV folds	Train samples at eachfold	Test samplesat eachfold	Accuracy
1	”Support VectorClassi- fier”	5	137	60	98
2	Logistic Regres-sion	5	137	60	100
3	”Na¨ıve BayesClassi- fier”	5	137	60	98
4	”Decision Tree Classi- fier”	5	137	60	98

TABLE VIII: Accuracy and MSE overview of ANN model

	Without hyperparametertuning	With hyperparametertuning
MSE	0.0623	0.0507
Accuracy	93	90

CONCLUSION

We have thus implemented various machine learning tech- niques to estimate the accuracy of posture for various exercisessuch as bicep curls, front kicks, boxing(jab punches), andsquats. We have used the MediaPipe library to detect theposture of our body and used the inbuilt pose estimator model to generate angles pertaining to specific exercises. Using heuristic functions, we determined a certain threshold for eachexercise which then helped us identify the correct and accuraterep performed by the user. This data is then fed to the models for predicting the state of the rep of a particular exercise

We found out that SVMs gave us the best results without hyperparameter tuning and Logistic Regression gave us the best with hyperparameter tuning. We also fed the same data toan Artificial Neural Network(ANN) which gave us acceptable results as well. Hence we opted for Logistic Regression with hyperparameter tuning for the machine learning pipeline. Poseestimation has made rapid progress in the last few years, with avariety of methods and techniques being suggested to preciselyestimate the pose of people or other objects. We have provideda thorough analysis of pose estimation in this study, covering the most widely used methodologies, and assessment metrics.

Future Scope

We plan to improve our algorithms and increase the accuracy and robustness of our model by increasing the sizeof our dataset and adding more custom data. Our goal is to make an application that will be ubiquitous and can be usedby everyone. We intend to incorporate various other exercises such as push-ups, deadlifts, etc. This application will havea plethora of features that will be personalized as well asgeneralized to the end user. Personalized features will also include gamification, personalized workout, and diet plans. Ultimately we plan to develop an all-in-one healthcare appthat will include pose estimation, personalized diet plans, workout plans, gamification, etc. We also aspire to add aVirtual and/or Augmented Reality interface that will providea very interactive user experience.AR/VR home automatedsystems can be very useful for people who do not have time to go to the gymnasium. This type of VR system in our homeswill be more beneficial and comfortable for us in the long run.

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