MONITORING 3D CARDIAC EXERCISE POSE USING R-CNN ALGORITHM

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Abstract*-Fitnessexercisesareverybeneficialtopersonalhealth and fitness; however, this proposed method, introduces Pose Trainer, an application that detects the user's exercise pose and providespersonalizeddetail.PoseTrainerusesthestateoftheart inposeestimationtodetectauser'spose,thenevaluatesthevector geometry of the pose through an exercise to provide useful feedback based on human pose. The recording of a dataset over 5 exercisevideosofcorrectformisdone,basedonpersonaltraining guidelines, and build geometric heuristic and machine learning algorithms for evaluation. A pose estimator called media pipe is used in this application. Media pipe is a pre-trained model composed of a multi-stage RCNN algorithm to detect a user's posture and counting the repetitions. This application evaluates the vector geometry of the pose through an exercise to provide helpful feedback. human posture in images or videos that shows thekeypointsintheoutputimage.ThePoseTrainerwiththePose Trainer application providing specific calorie burn data on the exercise form to the user and stored in the textfile.And also every exercise had set limit for completion once the exercise reached the limit the voice will be indicated.

Keywords-Pose Tracking, deep Learning, Recurrent Convolutional Neural Network.

I. INTRODUCTION

Exercises such as squats, dead lifts, and shoulder presses are beneficial to health and fitness, but they can also be very dangerous if performed incorrectly. The heavy weights involved in these workouts can cause severe injuries to the musclesorligaments.Manypeopleworkoutandperformthese exercises regularly but do not maintain the proper form (pose). This could be due to a lack of formal training through classes or a personal trainer, or could also be due to muscle fatigue or using too much weight. For this course project, seeking to aid people in performing the correct posture for exercises by building Pose Trainer, a software application that detects the user'sexerciseposeandprovidesusefulfeedbackontheuser's form, using a combination of the latest advances in pose estimation and machine learning. Our goal for Pose Trainer is tohelppreventinjuriesandimprovethequalityofpeople's workouts with just a computer and a webcam. The first step of PoseTraineruseshumanposeestimation,adifficultbuthighly applicabledomainofcomputervision.Givenvisualdata,which could be an RGB image and/or a depth map, a trained model predicts a person's joints as a list of skeletal key points. Pose estimation is critical for problems involving human detection and activity recognition, and can also aid in solving complex problemsinvolvinghumanmovementandposture.Thisproject use a state-of the-art pose estimation recurrent convolutional neural network, an Open Pose is used within Pose Trainer for inference.Thesecondpartofourapplicationinvolvesdetecting the quality of a user's predicted pose for a given exercise. By using heuristic-based and machine learning models approach, using the poses and instruction of personal trainers which use tomarkthekeypointsofthehumanjointsfortheposetracking process which is shown in the [Fig.1] the human joints are marked in the key points and other qualified professionals as the ground truth for proper form. Our full application consists of the previously described two main components, combined into an end-to-end application that can take a video of an exerciseandprovideusefullexerciseformfeedbacktotheuser.

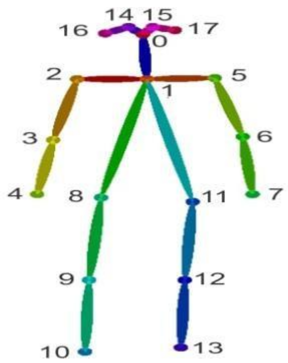


Fig 1: key points for the human joints, in this the body joints are marked with the points to track the human motion easily.

II.LITERATURESURVEY

Realtimemulti-person2Destimationusingpartaffinityfields. thistechniqueisdetecting2Dposeofhumaninaimageandthe method used in this application is non-parametric that refers as (PAFs). This work has placed first in inaugural coco2016 key point challenge and significantly exceeds onMPII.

Human pose Estimation with spatial contextual Information. pose networks are trained in a multi-stage manner and produce several auxiliary prediction for deep supervision. Cascade Prediction Fusion (CPF) and Pose Graph Neural Network (PGNN). This promote spatial correlation among joints and direct message passing between different joints is enabled and spatial relation is captured.

Aggregation for Human Pose Estimation. Deep convolutional neural networks are the technique which is used in this project to improve the accuracy of human pose estimation. Cascade Feature Aggregation (CFA) method is used. This project proposed a human pose estimation with well captured detailed information and global sematic information.

Deep High-Resolution Representation Learning for Human Pose Estimation. The human pose estimation problem with a focus on learning reliable high-resolution representations. Multi-scalefusionssuchthateachofthehigh-to-lowresolution representations receives information from other parallel representations over and over, leading to rich high-resolution representations. As a result of this more accurate and spatially more precise.

Light Track: A Generic Framework for Online Top-Down HumanPoseTracking.Single-personPoseTracking(SPT)and Visual Object Tracking (VOT) are incorporated into one unifiedfunctioningentity,easilyimplementedbyareplaceable single-person pose estimation module. A novel effective light- weight framework method is used. This is the first paper to propose an online human pose tracking framework in a top- down fashion.

Fast and accurate human pose estimation via soft-gated skip connections. Fully Convolutional Networks (FCNs), residual connections.forachievinghighaccuracy,andefficiency.Gated skip connections with per-channel learnable parameters. A hybrid network that combines the Hourglass and U-Net architectures which minimizes the number of identity connections. Achieves state-of-the-art results on the MPII and LSP datasets, show no decrease in performance when compared to the original Hourglassnetwork.

Challenges of Machine Learning Applied to Safety-Critical Cyber-Physical Systems. Machine learning is a technique used tocontrolofsafetyCriticalCyber-PhysicalSystem(CPS).ML- based control systems and their certification. This paperis intended as a basis for future holistic approaches for safety engineering of ML-based CPS in safety critical application.

A Review of Human Pose Estimation from Single Image. This paper is mainly focused on the human pose estimation method from a single two-dimensional image. And Deep learning method used in this paper.

Human pose estimation using with Deep Neural Networks. This paper presents a cascade of such DNN Regression which results in high precision pose estimation. The method used in this technique is Deep Neural Networks.

2D Human Pose Estimation: New Benchmark and State of the Art Analysis. In This paper a rich set of labels including position of human body joints, full 3D torso and head orientation, occlusion labels for joints and body parts, and activity labels are provided.

Real-Time Pose Estimation with Convolutional Neural Network. this paper is aimed for the use case for specific applications which gets the good accuracy of the background andposeswhicharelimited.Thispaperisbasedonthemethod ofconvolutionneuralnetworkforthisrealtimeposeestimation application. And its shows the accuracy of 96.8% with application specific data.

3D Pictorial Structures Revisited: Multiple Human Pose Estimation. The technique is to transform the single human pose to the multiple human pose estimation from 2D to 3D space.Thispapera3Dpictorialstructuresmodelisintroduced. In this paper a reduced state space by triangulation of correspondingpairsofbodypartsobtainedbypartdetectorsfor each camera view is created first. The HumanEva-1 and KTH Multiview Football II Datasets are used in thiswork.

Pose Trainer: Correcting Exercise Posture using Pose Estimation. This paper introducing the pose and provides personalized, detailed recommendations on user that can improve their form. This work uses pose trainer state of the art in pose estimation to detect a user’s pose. The geometric heuristic and machine learning algorithm is used for training over 100 exercise videos of correct and incorrect datasets.

Environment Adaptive RFID based 3D human pose Tracking with a Meta-learning approach. In this paper an environment adaptive solution for Radio -Frequency Identification (RFID) based 3D human skeleton tracking system is done. Meta learning approach is used for pose tracking. The RFID sensing is performed to validate the high adaptability and accuracy of the meta-pose system.

III. PROPOSEDSYSTEM

In this proposed system for pose estimation component, by utilizing a pre trained real-time system, called 32 media pipes, which plays a vital role in estimating human pose from video in various application such as physical exercise tracking and controlling body gestures. The 25 frames per second is converted into single frame. For pose estimation, the recurrent convolutional neural networks (RCNN) used to label RGB images. After experimentation with multiple state-of-the-art pose estimators, the pre-trained model 32 media pipe is chosen to use. Media pipe is a pre-trained model composed of a multi- stage RCNN algorithm to detect a user's posture and counting the repetitions. And this algorithm is used for pose estimation and counting the repetitions of exercise is done. The model is composed of a multi-stage RCNN with two branches, one to learn the confidence mapping of a key point on an image, and the other to learn the part affinity fields which is explain in[3]. The Pose Trainer application from a technical perspective as a pipeline system consisting of multiple system stages which is shown in [13]. Pose training starts from the user recording a video of an exercise, and ends. The pose points of humancan be calculated with the Threshold values. Pose Trainer system pipeline with the Pose Trainer application providing specific feedback on the exercise form to the user. raw signal is processed dynamically and calorie burn data's can be stored in the textfile.

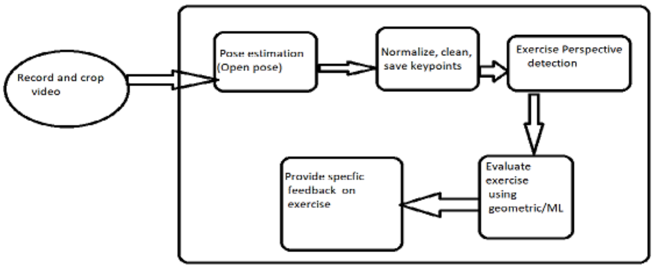


Fig 2: Pose Trainer system pipeline, as described in Technical Approach.

IV. WORKINGEXPLANATION

The above block diagram [Fig 3] of this project, we present a Pose Trainer application based on machine learning technique First, the user records a video of themselves performing a selected exercise. The video is recorded from a particular perspective that allows the exercise to be seen. However, there isnorequirementsoncameratypeordistancefromcamera,the user only needs to make sure that their body is visible. Then, the user trims the video such that it includes only the framesof the exercise. The key points can be extracted from the input images. After the key points extraction. The Pose Trainer application from a technical perspective as a pipeline system, consisting of multiple system stages Pose training starts from theuserrecordingavideoofanexercise,andends.PoseTrainer system32mediapipewiththePoseTrainerapplicationmark thepoints,theposecanbeestimatedandrepetitioncounting by using RCNN algorithm compared to dataset. As activity recognition and repetition count is calculated at real-time, raw signal is processed dynamically and calorie burn data's can be stored in the textfile.

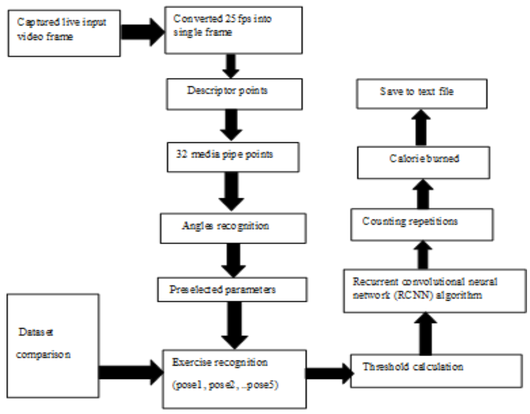


Fig 3: System architecture of pose estimation,

At first, the Fig [2] shows the video is recorded by the user by themselves from performing the selected task or exercise. However,therearenorequirementsoncameratypeordistance from camera Then the captured images are converted 25 frame per second into single frame. The descriptor points are used to calculate the key points of the joints, a descriptor is computed for the aligned point cloud based on how its 3D points are spatially distributed. Next angle recognition is done when the user is performing. By using the preselected parameter the exercise recognition can be done. The datasets with are stored in the input are compared and after the comparison process the threshold value is calculated by using the geometric values. Then the (RCNN) Recurrent Convolutional Neural Network Algorithm is used to compare the exercise and also counts the repetitions of the exercise done by the user and after this the feedback for the user are stored in the text fileformat.

V. RECURRENT CONVOLUTIONAL NEURAL NETWORK ALGORITHM(RCNN)

Recurrent convolutional Neural Network (RCNN) is a type of Neural Network where the output from previous steps are feed as input to the current step. In traditional neural networks, all the inputs and outputs are independent of each other, whenit is required to predict the pose of human, the hidden layer is located between the input and output of the algorithm in which the function applies weights to the input and directed to the activation function. The hidden layer performs as a nonlinear transformation of the inputs entered into the network. The hidden layer captured more complexity with every layer by discovering relationships between features in the input. The main and most important feature of RCNN is Hidden state, which remembers some information about a sequence. RCNN havea"memory"whichremembersallinformationaboutwhat has been calculated. It uses the same parameters for eachinput as it performs the same task on all the inputs or hidden layers producetheoutput.Thisreducesthecomplexityofparameters, unlike other neuralnetworks.

A recurrent convolutional neural network (RCNN) is a classof artificial neural networks where connections between nodes formadirectedorundirectedgraphalongatemporalsequence. Derived from feedforward neural networks, RCNNs can use their internal state (memory) to process variable length sequences of inputs. The backpropagation algorithm of an artificialneuralnetworkismodifiedtoincludetheunfoldingin timetotraintheweightsofthenetwork.Thisalgorithmisbased on computing the gradient vector and is called back propagation in time or BPTT algorithm for short. However, RCNNs suffer from the problem of vanishing gradients, which hampers learning of long data sequences. The gradients carry information used in the RCNN parameter update and when the gradient becomes smaller and smaller, the parameter updates becomeinsignificantwhichmeansnoreallearningisdone.The RCNNunitinTensorFlowiscalledthe“RCNNcell”.Itretains information from one-time step to another flowing through the unrolled RCNN units. Each unrolled RCNN unit has a hidden state. The current time steps hidden state is calculated using information of the previous time steps hidden state and the current input. In Fig 4 the recurrent neural network layers are shown

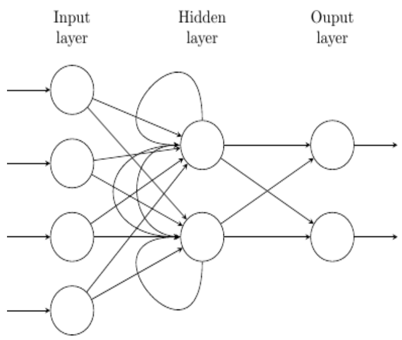
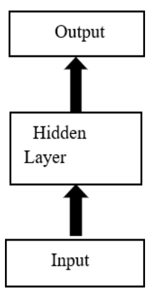


Fig 4: Recurrent Neural Network layers

Convertabstractsfromlistofstringsintolistoflistsofintegers (sequences)



- Create feature and labels from sequences.Build LSTM model with Embedding, LSTM, and Dense layers.Load in pre-trainedembedding.Train model to predict next work insequence

In a nutshell, RCNN is explained as it contains some internal statethatgetsupdatedeverytimestep.Duringoutputsequence prediction, the knowledge of the past is used through hidden states. It finds its application is areas such as speech recognition, language modelling, machine translation, building chat bots. When you feed a batch of data into the RCNN cell it starts the processing from the 1st line of input. Likewise, the RCNN cell will sequentially process all the input lines in the batch of data that was fed and give one output at the endwhich includes all the outputs of all the input lines. Recurrent Neural Networks (RCNN) are a class of Artificial Neural Networks thatcanprocessasequenceofinputsindeeplearningandretain its state while processing the next sequence of inputs. Traditional neural networks will process an input and move onto the next one disregarding itssequence.

RCNN Algorithm Formula

- $h_t = f(h_{t-1}, x_t)$

Where

h_t = current state.

h_{t-1} = previous

state. x_t = input

state.

- $h_t = \tanh(W_{hh}h_{t-1} +$

$W_{xh}x_t)$ Where

W_{hh} = weight at recurrent

neuron W_{xh} = weight at input

neuran

- $Y_t =$

$W_{hy}h_t$Where

Y_t = output

W_{hy} = weight at output layer

A. 32 Mediapipe

Media Pipe is a an open-source framework from Google for building multimodal (e.g., video, audio, any time series data), cross platform (i.e., Android, iOS, web, edge devices) applied ML pipelines. It is performance optimized with end-to-end on device inference in mind. Media Pipe is able to achieve its speed that is used in GPU acceleration and multi-threading. The multi-threading and GPU acceleration allow newerphones torunawaywithframes,oftenbeingatFPStoohightoseewith thehumaneyeMediapipeisacross-platformlibrarydeveloped byGooglethatprovidesamazingready-to-useMLsolutionsfor computervisiontasks.OpenCVlibraryinpythonisacomputer vision library that is widely used for image analysis, image processing, detection, recognition, etc., Roughly a year ago, Google open-sourced Media Pipe, a framework for building cross-platform AI pipelines consisting of fast inference and media processing (like video decoding) Media Pipe is able to achieve its speed thanks to the use of GPU acceleration and multi-threading. The multi-threading and GPUaccelerationallownewerphonestorunawaywithframes, often being at FPS too high to see with the humaneye.

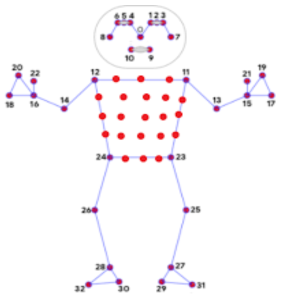


Fig 5: media pipe

The solution utilizes a two-step detector-tracker ML pipeline, proven to be effective in our MediaPipe Hands and MediaPipe Face Mesh solutions. Using a detector, the pipeline first locates the person/pose region-of-interest (ROI) within the frame. The tracker subsequently predicts the pose landmarks and segmentation mask within the ROI using the ROI-cropped frame as input. Note that for video use cases the detector is invoked only as needed, i.e., for the very first frame and when the tracker could no longer identify body pose presence in the previous frame. For other frames the pipeline simply derives the ROI from the previous frame's pose landmarks.The pipeline is implemented as a MediaPipe graph that uses a pose landmark subgraph from the pose landmark module and renders using a dedicated pose renderer subgraph. The pose landmark subgraph internally uses a pose detection subgraph from the pose detection module. By above Fig.5. Optionally, MediaPipe Pose can predicts a full-body segmentation mask represented as a two-class segmentation (human or background).

B. PoseTracker

Pose estimation is a computer vision task that enables machines to detect human figures and understand their body pose in videos and images. It helps machines determine, for example, where the human knee is located in an image. Pose estimation focuses on estimating the location of key body joints and cannot recognize the individual's identity in a video or image. posetrackertoidentifyandtrackexerciseposebyapplyingthe algorithm is used for the persons exercise recognition to detect the name of the appeared exercises, and counter to count and indicate the correct and incorrect repetitions. Pose Tracking is the task of estimating multi-person human poses in videos and assigninguniqueinstanceIDsforeachkeypointacrossframes. The pose tracking used in pose estimation in [16]. Accurate estimation of human key point-trajectories is useful for human action recognition, human interaction understanding, motion capture and animation. Human pose estimation from video plays a critical role in various applications such as quantifyingphysicalexercises.InFig6thejointsoftheleg,bodyand hands are detected using pose trackingmethod.

Pose estimation models track and measure human movement. They can help power various applications, for example, an AI-based personal trainer. In this scenario, the trainer points a camera at an individual performing a workout, and the pose estimation model indicates whether the individual completed the exercise properly or not. A personal trainer application powered by pose estimation makes home workout routines safer and more effective. Pose estimation models can run on mobile devices without Internet access, helping bring workouts (or other applications) to remote locations via mobile devices.Pose estimation can help create realistic and responsive augmented reality (AR) experiences. It involves using non-variable key points to locate and track objects, such as paper sheets and musical instruments. Rigid pose estimation can determine an object's primary key points and then track these key points as they move across real-world spaces. This technique enables overlaying a digital AR object on the real object the system is tracking. Pose estimation can potentially help streamline and automate character animation. It requires applying deep learning to pose estimation and real-time motion capture to eliminate the need for markers or specialized suits for character animation. Pose estimation based on deep learning can also help automate capturing animations for immersive video game experiences. Microsoft's Kinect depth camera popularized this type of experience. 3D human pose estimation predicts the locations of human joints in 3D spaces. It works on monocular images or videos, and helps provide 3D structure information on the human body. It can power various applications, including 3D animation, 3D action prediction, and virtual and augmented reality. 3D pose estimation can use multiple viewpoints and additional sensors, such as IMU and LiDAR, and work in conjunction with information fusion techniques. However, 3D human pose estimation faces a major challenge. Obtaining accurate image annotation is time-consuming, while manual labeling is expensive and not practical. Computation efficiency, model generalization, and robustness to occlusion also pose significant challenges.

Fig 6: Pose Tracker

VII. IMPLEMENTATION

In this project, the implementation done by recoding the video of exercise which is done by the user, and for each exercise 5 task are allotted after when the person doing the exercise, the application starts to count the repetition of the task done bythe user in front the camera. After completing the task system storestheinformationoftheexercisecompletedbytheuser.gives the final feedback which is how much calories areburnt when after finishing the task. And the information's of the output are stored in the text file format for the user. For this implementation process the dataset are taken and trained by using the RCNN algorithm, by using this algorithm in thedeep learning method the exercise are compared and useful feedbacks aregained.

C. Datasets

Human pose estimation from video plays a critical role in various applications such as quantifying physical exercises, sign language recognition, and full-body gesture control. For example, it can form the basis for yoga, dance, and fitness applications. It can also enable the overlay of digital content and information on top of the physical world in augmented reality. Media Pipe Pose is a ML solution for high-fidelity body pose tracking, inferring 3D landmarks and background segmentation mask on the whole body from RGB video frames utilizing our Blaze Pose research that also powers the ML Kit Pose Detection API.

- Collect image samples of the target exercises and run pose prediction on them,
- Convert obtained pose landmarks to a representation suitable for the k-NN classifier and form a training set using these Collabs,
- Perform the classification itself followed by repetition counting (e.g., in the ML Kit quick start app).

To build a good classifier to find appropriatesamples should be collected for the training set, about a few hundred samples for each terminal state of each exercise ("up" and "down" positions for push-ups). It's important that collected samples cover different camera angles, environment conditions, body shapes, and exercise variations. After that, you'll be able to test the classifier on an arbitrary video right in the Collab. To convert pose landmarks to a feature vector, we use pairwise distances between predefined lists of pose joints, such as distances between wrist and shoulder, ankle and hip, and two wrists. Since the algorithm relies on distances, all poses are normalized to have the same torso size and vertical torso orientation before the conversion. The Media Pipe Holistic pipeline integrates separate models for pose, face, leg and hand components, each of which are optimized for their particular domain. However, because of their different specializations, the input to one component is not well-suited for the others. The pose estimation model, for example, takes a lower, fixed resolution video frame (256x256) as input. But if one were to crop the hand and face regions from that image to pass to their respective models, the image resolution would be too low for accurate articulation. The solution utilizes a two-step detector-tracker ML pipeline, proven to be effective in our Media Pipe Hands and Media Pipe solutions. Using a detector, the pipeline first locates the person/pose region-of-interest (ROI) within the frame. The tracker subsequently predicts the pose landmarks and segmentation mask within the ROI using the ROI-cropped frame as input. Note that for video use cases the detector is invoked only as needed, i.e., for the very first frame and when the tracker could no longer identify body pose presence in the previous frame. For other frames the pipeline simply derives the ROI from the previous frame's pose landmarks.

D.Key point Descriptor

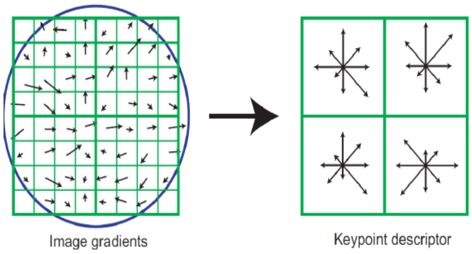


Fig. 7: Key Point Descriptor

Binary image descriptors encode patch appearance using a compact binary string. The hamming distance in this space is designed to follow a desired image similarity measure typically sought to be invariant to scene illumination and viewpoint changes. A feature descriptor is an algorithm which takes an image and outputs feature descriptors/feature vectors. Which is Fig 7. Features descriptors encode interesting information into a series of numbers and act as a sort of numerical "fingerprint" that can be used to differentiate one feature from another. the coordinates of the descriptor and the gradient orientations are rotated relative to the key point orientation φ.

VIII.EXPREMENTALRESULT

Fig.8: Task Counting

Pose tracking with RCNN algorithm. By using this algorithm the pose tracker can tracks the body points for the purpose to track the counting repetition of exercise done by the user. In this process the media pipe is used as a pose tracking method. Which is shown in Fig.8. after the completion of the task the voice alert will be indicated.

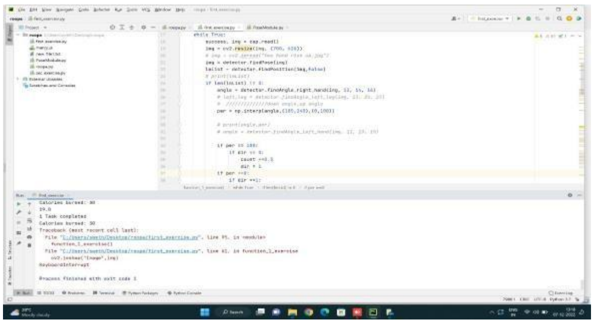


Fig.9: Exercise feedback

In this the task which is completed is shown here Fig.9. By calculating the exercise done by the user. In this process the only the correct exercise done by the user will be taken, if the user gives the wrong pose the program will not take it as a count.

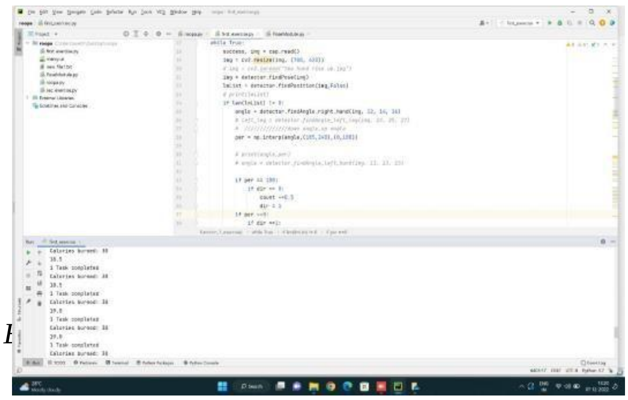


Fig 10: sending feedback in textformat

After the completion of the exercise how much calories burnt by the user is given as a output and stored as a text format as a output. Which is shown in Fig.10. and its stores the text feedback for the future use for the user.

VIII.CONCLUSION

In this project, we introduce Pose Trainer, an end-to-end computer vision application that uses pose estimation and repetition counting, visual geometry, and machine learning to providepersonalizedfeedbackonfitnessexerciseform.Weuse the output of pose estimation to evaluate videos of exercises through human pose key points. We work with five different exercises, recording training videos for each, and use both geometric heuristic algorithms to provide personalized feedback on specific exercise improvements, as well as machine learning algorithms to automatically determine posture estimation and repetition counting using only labeled input videos. we developed two workout model, here the input frames are converted into signal frame which is used for accurate results, and the person pose tracking will be done by using 32 media pipe points will be noted and detected, the preselected angle will be fixed based on threshold. And after compilation of task for each exercise the alert sound will be indicated.

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