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Human Pose Detection System Using Machine Learning

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Abstract: Human pose detection is one of the essential factors in many surveillance-based applications such as fall detection, human-computer interaction activities, sports and fitness, motion or movement analysis, robotics, and many other 'Artificial Intelligence projects and applications. In this survey, we aim to cover the methods that are used before, for human pose detection- single person or multiple people, and examine their efficiency using required parameters, and their real-time compatibility. We will compare and discuss the different methods and technologies used for posture detection and their results. This research can be used to improve the results of systems that use pose detection as their primary parameter, hence can be very helpful for many life-saving applications such as fall detection. We also aim to use this research to develop an efficient model for human pose detection using deep neural networks. The model works on both images and video Human pose detection is one of the essential factors in many surveillance-based applications such as fall detection, human-computer interaction activities, sports and fitness, motion or movement analysis, robotics, and many other 'Artificial Intelligence projects and applications. In this survey, we aim to cover the methods that are used before, for human pose detection- single person or multiple people, and examine their efficiency using required parameters, and their real-time compatibility. We will compare and discuss the different methods and technologies used for posture detection and their results. This research can be used to improve the results of systems that use pose detection as their primary parameter, hence can be very helpful for many life-saving applications such as fall detection.
We also aim to use this research to develop an efficient model for human pose detection using deep neural networks. The model works on both images and videos. The model is built for single-person pose estimation with the help of Machine Learning.
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Keywords: *Human pose detection, deep learning, machine learning, Human pose estimation, python, CNN, DNN.*

1. Introduction

Human pose detection, also known as human pose estimation, is a significant task in computer vision and machine learning. The primary goal of human pose detection is to accurately identify the position and orientation of the human body joints. With the increasing demand for intelligent human-computer interaction and human behavior analysis, accurate and efficient human pose detection algorithms have significant potential applications in areas such as robotics, sports analysis, healthcare, and entertainment. The traditional human pose detection methods rely on handcrafted features and shallow machine learning models, which limit their accuracy and robustness in handling complex poses and cluttered backgrounds. Recently, the emergence of deep learning-based techniques has led to significant improvements in human pose detection performance, making it a hot research topic in computer vision and machine learning.

1.1. Motivation

Human pose detection is an essential task for many applications such as action recognition, tracking, and motion analysis. Traditional methods suffer from limitations, such as low accuracy, high computational complexity, and low robustness to occlusions and cluttered backgrounds. On the other hand, deep learning-based methods have shown remarkable success in addressing these challenges and achieving state-of-the-art performance in human pose detection. Therefore, a comprehensive survey of recent advancements in human pose detection using machine learning/deep learning/computer vision is crucial to understand the current state-of-the-art techniques and to identify the future research directions.

1.2. Objective

The primary objective of this survey paper is to present a comprehensive review of recent advancements in human pose detection using machine learning/deep learning/computer vision. Specifically, we aim to achieve the following goals:

Provide an overview of the traditional human pose detection

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methods and their limitations.

Introduce the deep learning-based techniques for human pose detection, including Graph Neural Networks (GNNs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs).

Discuss the deep learning-based human pose detection algorithms, including the Single Person Pose Estimation (SPPE) and Multi-Person Pose Estimation (MPPE) methods.

Compare and evaluate the performance of different human pose detection algorithms based on various metrics such as accuracy, speed, and robustness.

Identify the challenges and future research directions for human pose detection using machine learning/deep learning/computer vision.

1.3. Organization

The paper below is organized as follows. Section 2 provides an overview of the traditional human pose detection methods and their limitations. Section 3 introduces the deep learning-based techniques for Single person human pose detection, including direct regression and heatmap and 3D-pose detection using CNNs, RNNs, and GNNs . Section 4 discusses the Multiple-Person or multi-person human pose detection algorithms, including bottom-up top-down, and hybrid methods. compares and evaluates the performance of different human pose detection algorithms based on various metrics. Section 5 gives an overview of the proposed system. Section 6 Performance metrics for human pose detection using machine learning/deep learning/computer vision. Finally, Section 7 concludes the paper with a summary of the key findings and contributions.

2. Literature Survey

Pose estimation is a computer Vision based method that helps the machine to predict a human pose or body gesture from images and videos. It helps to locate the knee, eyes, shoulder, and estimate, key body points of the human body. Pose estimation is mostly used in augmented reality, Gaming, animation, Robot Training, and Athlete pose detection. In traditional object detection, people are only considered as bounding boxes. but pose estimation provides much more details than traditional object detection. [15] Recently, numerous methods are available for pose estimation image processing is one the renowned method, as the body's appearance changes continuously due to clothing and arbitrary occlusion of human pose estimation becomes a difficult task in such cases.

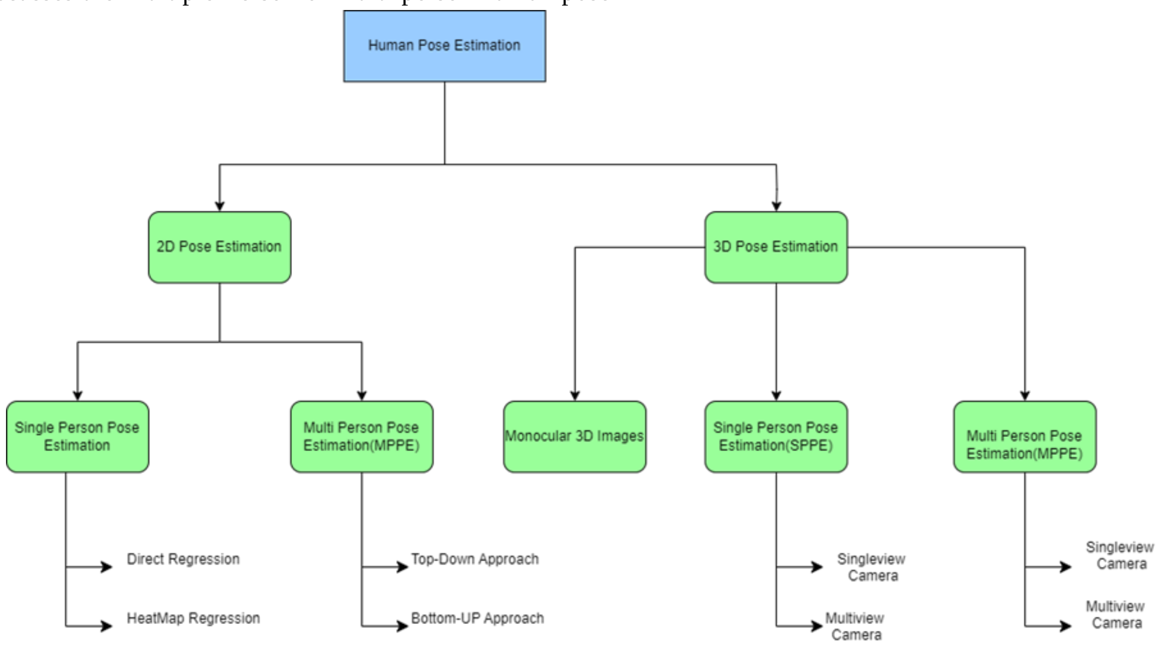

Fig 1 Approaches of Human Pose Estimation

Hence image processing does not give the accurate result for this. Earlier Hand-Crafted features like HOG (Histogram of Oriented Gradient) were used but this method is not able to give the accurate locations of body parts. Nowadays, In the field of Computer Vision pose detection has become an active topic of study because of its lot of applications and usefulness. In this paper, we mainly focus on pose estimation using Computer Vision. There are a lot of surveys done by the researchers, Qi Dang has given a deep survey of deep learning-based methods for 2D human pose estimation [15]. In this approach, he classified all human pose estimation methodologies into two parts single person or group of persons. Single-person pipelines can be solved by direct regression and heat map-based methods. Whereas Top-down Approach and Bottom-up approach can be used to solve multiple-person pipelines. In the top-down, first, detect all persons from the image and then perform the single-person approach. whereas the bottom-up method is similar to the top-down method but it is performed in reversed order. Eralda Nishani and Betim Cico have reviewed the existing research about the implementation of Computer Vision in pose estimation that is based on CNN (Convolutional Neural Network) and Deep Learning Algorithms and found that RNN (Recurrent Neural Networks) can be improved and used in human pose detection [2]. Jincheng Yu and their team proposed a new vision based on the deep learning model called a robotic grasping system that recognizes different objects and also estimates their poses. For this, they used Max pooling convolutional neural network. Jamie Shotton and Ross Girshick have designed two new approaches to predict the 3D positions of body joints from single-depth images [] for this they designed two algorithms for body part classification and offset joint regression both algorithms use decision forest trees and deep in-variant image features. Pose estimation can be effectively used in the fall detection system. Fall detection is a system that monitors the video frames and tries to figure out the poses if the machine finds out the falling behaviour then it will inform the caretaker, so here pose estimation techniques play a very important role. Yangsen Chen used this method for fall detection combined with the Yolov5 algorithm [12], A classifier based on machine learning classifiers and deep learning, Sidrah Liqat and Kamran Arshad proposed a novel hybrid approach to

predict the posture. This hybrid approach eventually increases the performance of machine learning and Deep learning algorithms [10].

3. Single-person Pose Estimation

Fig. 1 given below shows the approaches for human pose detection taxonomically. They are explained below in this paper.

Basically, there are two scenarios to develop the project of pose estimation: a) Single person pose estimation and b) Multiple people pose estimation at one. Both of them have their own applications at different places and amount of processing to be done. In scenarios where only one person is being monitored such as an elderly person at home, or at a personalized gym, a lot of processing required in a multiple-person analysis approach can be avoided, and better quality of estimation can be achieved. Now, we'll discuss, how this approach can be achieved. Now, in this approach of pose estimation we either can give an image or a video for the analysis. Previously we needed to provide a rough outline of the human for better performance but nowadays that can be achieved directly through deep neural networks (DNN). DNN applies the approach where it directly connects the key points. Overall there are a few methods for the single-person pose detection approach:

3.1 Direct Regression

Based on the Direct regression framework several:

works were proposed Alexander Toshev, and Christian Szegedy suggested a cascade of DNN regressors that results in high-precision pose estimation. They proposed a system in which the key points were directly detected and the from the features. whilst it was a little difficult foe model to achieve the good performance , as in order to increase the performance of the model carriers used a method of feeding those errors data to the machine for more accurate results. Other than these approaches structure-aware approach which is also known as the compositional approach for pose detection is used by Sun et al. In this he proposed a system unlike the above approaches of regression based on the keypoint, it works on the bone recognizing than joints. This approach was primitive but stable and easy. Then one more unique approach was made by Luvizon et al. He converted the heatmap keypoints into the coordinates and used the loss function based on the keypoints error to calculate the results. This approach was giving accuracy near to the heatmap-based approach.

3.2 Heatmap

In key point regression in order to identify the exact point it increases the complexity of the problem as well as sensitivity and causes instability so researchers proposed an alternative approach for the key point regression called as Heat Map based regression. Heat Maps are basically the graphical representations of data that uses color-coded system. In this framework from each pixel of the image we have to calculate the probability of the existence of key point. It generates the output as a heatmap indicating the probabilities the main purpose of heatmap is to visualize the volume. Figure 1 represents the implementation of heatmap approach stepwise.

'Convolutional pose machines' paper proposed by Varun Ramkrishna, and Yaser Sheikh [16].It uses convolutional pose machine architecture that uses heatmaps iteratively estimate the pose. Angjo , Michael Black, David Wjacobs, and Jitendra Malik proposed a method for 3D human pose human pose estimation from a single color image using heatmaps [17]. Heatmap-based regression suffers mainly from two problems: decoding problem and ground truth. Overall heatmaps have become a very popular and effective tool for pose estimation

3.3 3D Pose Estimation

Working with a 3D model is more complex than the other 2D methods because 3D models need the key points detection from regression, which are not much accurate. There are mainly four methods to implement this method [13]. The first takes the input from the camera or images. Lee et al first parameterize the body parts by truncated cones. Then he optimized the body part's rotation to avoid or reduce the discrepancy between the model and the actual image. The most difficult part in this system is the ambiguity caused while recognizing the body parts/ joints when the person is doing the twofold 'backward/forward' flipping which leads to an exponential number of minima. Then Rehg, Kanade, and Morris realized the ambiguity and to overcome those they proposed a new model, the '2-dimensional scaled prismatic model'. This model had very few ambiguities as compared to the others. Triggs and Sminchisescu applied the inverse kinematics in order to explore the complete configuration and increased performance overall basic work done till the time. After this, they also worked on minimizing the local minima causing ambiguity. They build a road map to the nearby minima which are linked by transition pathways found while looking for co-dimension saddle points. Now let's talk about modeling

in 3D pose estimation. There are three types of models for Human body modeling as shown in figure 2:

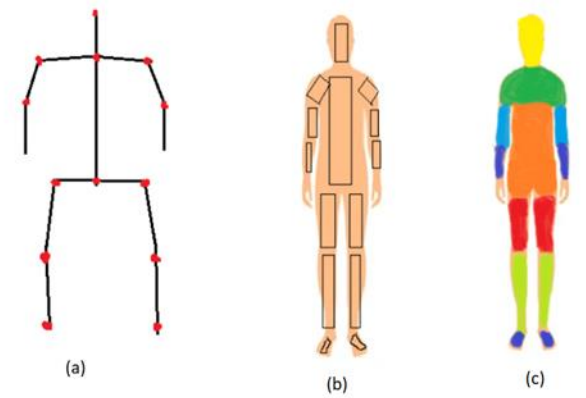

Fig 2 Types of Human body modeling (a) Kinematic, (b) Planar, (c) Volumetric model

3.3.1 Kinematic Model

This is also known as the skeleton model. As the name suggests this model includes extracting features like a set of joints and limbs and the orientation of the body. so this model helps in finding the relation and orientation between different body parts. But it gives poor performance when it comes to recognizing the shape information or texture.

3.3.2 Planar Model

It's also called a contour-based model. is used for two-dimensional pose estimation. This model recognizes the shape or contour of the body. It represents the body parts with rectangles. It's a popular example of an active shape model. It is used for capturing the graph of the full human body and the above-mentioned silhouette deformations using PCA(Principle Component analysis.)

3.3.3 Volumetric Model

This is the most realistic model in 3D pose estimation. As the name suggests it takes the volumetric analysis of the full human body. It is a deep-learning-based framework. There are mainly models available such as GHUM. They've fully trained with over 60,000 human body shapes with different angles.

Table 1. Comparison Chart of Approaches of Single-Person Pose Estimation

Sr. No	***Methods***	***Advantages***	***Disadvantages***
1	Direct Regression Method	Direct and quick, It is trained very well with a wide variety of data.	Mapping in this method is complex.
		With Little changes, it can be applied to 3D methods.	Can't be applied in multiple-person scenarios
2	Heatmap-Based Method	Better to understand	It needs more memory for high-resolution capture.
		Better in more complex data problems and scenarios.	It's difficult to make it work for a 3D model

4. Multiple-Person Pose Estimation

To detect multiple people in an image is a challenging task, because of varying poses and occlusions between individuals. Also in this type of model, multiple factors need to be considered such as varying number of people in the frame. Because when it comes

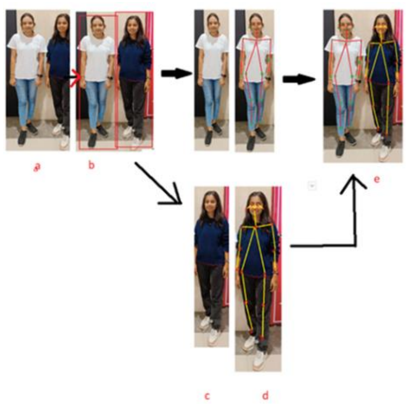

Fig 3 The Illustration of Top-Down Approach

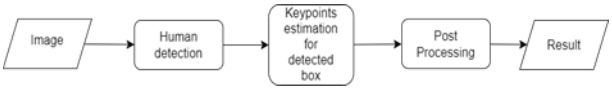

Fig 4 The Framework of Top-Down Approach

to the real-life use cases these are factors that need to be considered. For multiple-person pose estimation, multiple methods were proposed. We will discuss some of them in this paper.

4.1 Top Down Approach

In the top-down approach using object detection methods first it detects all the people in an image, and then it estimates the pose for each and every person. It uses one of the popular methods called open pose system, that uses a multistage pipeline, to estimate key-points for each person. Then it applies greedy algorithm to group the keypoints into body parts and person.The framework of the top-down approach is shown in Fig4. The Illustration of the top-down approach is shown in Fig 3. In Fig 3(b) human is detected from the given input image, in Fig 3(c) Keypoints are estimated from the detection box in Fig 3 (e) results are shown.

Many researchers use this approach multi-Person pose estimation. Bin Xiao, Haipinj Wu and Yichen Wei use top-down approach in their paper [50]. In their paper called "Simple Baseline For Human pose Estimation ". Paper proposed by Hao-Shu Fang, Shuqin Xie, Yu wing tian proposed a top-down approach that uses faster RCNN to detect people and then estimates the poses using two-stage network [51]. similarly, paper proposed by Mohammad Kocabas, saliz Karagoz given a top down approach that uses mask RCNN model to detect people and residual network for pose estimation [52].

4.2 Bottom-Up Approach

Bottom-Up approach is the opposite of top-down approach. It first detect keypoints individually in an image and then group them into poses. One of the method to do this is associative embedding approach that learns a similarity matrix between the keypoints and group them into poses. Actually it uses graph clustering algorithm.Fig 6 depicts the framework of Bottom up Approach. The illustration of Bottom-Up Approach is shown in Fig 5,in the first part input image is given, then in 5b keypoints detection of the personis done by the model, in 5c all the detected keypoints are joined to form human instance.

The bottom-up approach for multiple person pose estimation has been widely used in research

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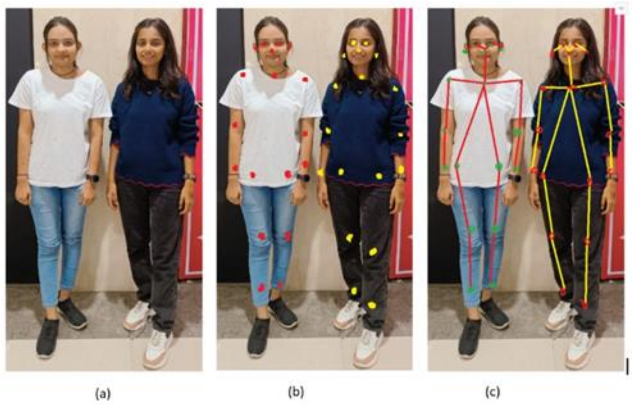

Fig 5 The Illustration of Bottom-up Approach

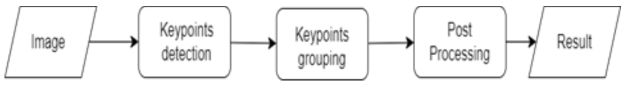

Fig 6 The Framework of Bottom-Up Approach

papers.Some of the examples are paper published by Zhe Cao, Thomas Simon and Yaser Sheikh has given a detailed information in their paper [53].Alexander Newell, Kaiyu Yang proposes a deep grouping approach that uses a convolutional neural network to group individual keypoint into poses [54]. Bin Xiao extends a topdown approach with bottom-up. Post processing steps that refines the post estimate by considering the interdependence of keypoint [50]

So overall bottom-up approach has been a popular choice for multiple person pose estimation.And many researcher have explored various ways to improve the efficiency and accuracy.

4.3 Hybrid Approach

In the hybrid approach top-down and bottom-up approach is combined one of the example of this approach is mask RCNN based approach, where object detection is used for detecting people , and bottom-up method is used for pose-estimation.

The advantage of hybrid approach is it gives the robustness of the top-down approach for detecting the people in an image and for estimating the poses. It gives fined grained accuracy of bottom-up approach, but it can be computationally expensive as it is a two step process. Also it involves multiple networks.

4.4 Multi-stage Approach

Multi-stage approach iteratively refines pose estimates. integral regression networks is one of the examples of a multistage approach to refine the location and scale of keypoints.

Table 2. Comparison Chart of Approaches of Multiple-Person Pose Estimation

Sr. No	***Methods***	***Advantages***	***Disadvantages***
1	Top-down Method	Computationally Efficient	Less accurate than other approaches Finds it hard to handle complex poses
2	Bottom-Up Method	Easily handles complex body poses and movements More accurately, when the people are closely spaced	Computationally expensive than other approaches Finds hard to handle varying numbers of people in the image.
3	Hybrid	It can handle complex poses and body movements. The combined strength of both the above models	Computationally expensive In some cases, it can be less accurate than the above two models. Increases the complexity of the system as it requires multiple networks and stages

5. Proposed System Methodology:

Human pose estimation is a fundamental task in computer vision that involves determining the spatial locations of key body joints in an image or video. Accurate pose estimation is crucial for various applications, including activity recognition, gesture analysis, and human-computer interaction. In this study, we propose a robust approach for single pose estimation using OpenCV, a widely adopted computer vision library.

Our method leverages the power of OpenCV's pre-trained deep learning models, specifically the OpenPose model, to detect and localize human body joints. We utilize the multi-stage convolutional neural network architecture of OpenPose to extract features and predict the keypoint locations accurately. By employing OpenCV's image processing and computer vision algorithms, we refine the detected pose keypoints and improve their accuracy.

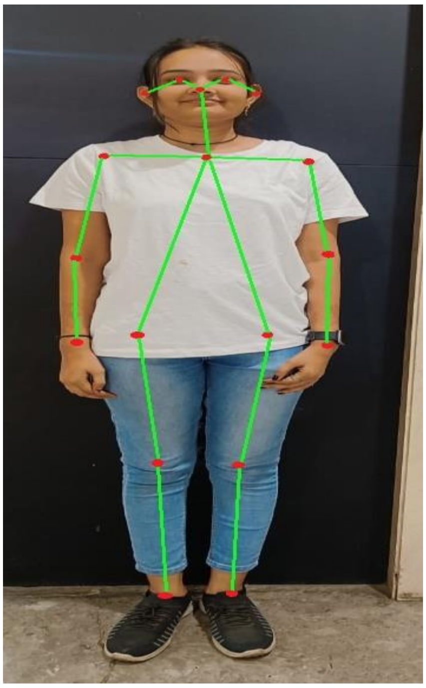

Fig 7 Result of proposed system

5.1 Pseudo Code

I. Defined the body parts of the human body in order to point.
II. Then pair these elements in order to find the pose in the skeleton-type format.
III. Input the image or video and take its width and height as frame dimensions parameters.
IV. Insert the body parts dataframe into two different data frames and connect them with the line if the pair exists in the pair parts dataframe.
V. Then fill those lines and ellipse them with colors.
VI. Now we can simply get the pose by simply calling the function.

For the video we have a number of frames so firstly we check for the same frame dimensions in every frame

If the size differs it resizes it to the previous one.

a) Then we import FOURCC video codec and to write to the video.
b) That takes a filename, fourcc , fps, and frame size as input in order to write to the video.
c) Then we open the video And starts detecting human body poses until the file end and write an output.avi file.
d) This file is nothing but our result playing with the given fps speed.

6. Performance Metrics

Calculating the performance of this system is difficult, many factors need to be considered.Unlike other applications in

ML with numerical input and outputs this is another this to calculate into the numbers. One of the methods used for this is to calculate correctly predicted body parts. This method is called as Percentage of Correctly estimated body Parts (PCP).

Then another method is to calculate correctly predicted keypoints. This metric has two variants, namely PCK and PCKh. This method checks if the predicted keypoint lies in the alpha-max(w,h)pixels of the actual true keypoint.

Then another superlative method is introduced in this which along with scale also considers per point constant. This helps the model to take control over falloff.This method is named as Object Keypoint Similarity(OKS) and AP of the OKS

7. Conclusion

We briefly studied various algorithms and methods used for human pose estimation. There are various investigations going on in this field but the results are not satisfactory.Each and every approach has its own pros and cons. The performances of these approaches and algorithms are still under verification and researchers are working on these methods to make it faster and more efficient. The algorithm used in this system is slow and not up to the requirement of real-time applications. There the speed should be achieved.There is already a work done in the network accelerating and network compression. That should be applied in this system. but these networks need high-resolution feature maps. So this field is needed to explore further.

Then the next factor is datasets. The available data for training is huge but though the ambiguities exists due to the lack of the proper training when it comes to unbalanced datasets with complicated poses which are hard to detect.

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