

Pose Estimation Using Deep Learning

*A mini project report submitted in partial fulfilment of the requirements for
the award of the degree of*

Bachelor of Technology

in

Computer Science & Engineering

Submitted by

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CERTIFICATE

This is to certify that the report entitled “**Pose Estimation Using Deep Learning**” is a bonafide record of the mini project submitted by **Aman K. Shihab(FIT19CS015)**, in partial fulfilment of the requirements for the award of the degree of Bachelor of Technology (B.Tech) in Computer Science & Engineering during the academic year 2021-22.

Staff in Charge

Project Guide

Dr. Jyothish K John
Head of the Department

ABSTRACT

Single-person human pose estimation facilitates markerless movement analysis in sports, as well as in clinical applications. Still, state-of-the-art models for human pose estimation generally do not meet the requirements of real-life applications. The proliferation of deep learning techniques has resulted in the development of many advanced approaches. However, with the progresses in the field, more complex and inefficient models have also been introduced, which have caused tremendous increases in computational demands. To cope with these complexity and inefficiency challenges, we propose a novel convolutional neural network architecture, called EfficientPose, which exploits recently proposed EfficientNets in order to deliver efficient and scalable single-person pose estimation. EfficientPose is a family of models harnessing an effective multi-scale feature extractor and computationally efficient detection blocks using mobile inverted bottleneck convolutions, while at the same time ensuring that the precision of the pose configurations is still improved. Due to its low complexity and efficiency, EfficientPose enables real-world applications on edge devices by limiting the memory footprint and computational cost. The results from our experiments, using the challenging MPII single-person benchmark, show that the proposed EfficientPose models substantially outperform the widely-used OpenPose model both in terms of accuracy and computational efficiency. In particular, our top-performing model achieves state-of-the-art accuracy on single-person MPII, with low-complexity ConvNets.

Contribution by Author

The model was fine-tuned using the Leeds Sports dataset. We observed some points increase in accuracy of the model. Work is progressing currently on obtaining dataset to finetune it for Physiotherapy pose detection and correction.

Student Name

ACKNOWLEDGEMENT

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Aman K. Shihab

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Chapter 1

Introduction

1.1 Overview

Single-person human pose estimation (HPE) refers to the computer vision task of localizing human skeletal keypoints of a person from an image or video frames. Single- person HPE has many real-world applications, ranging from outdoor activity recognition and computer animation to clinical assessments of motor repertoire and skill practice among professional athletes. The proliferation of deep convolutional neural networks (ConvNets) has advanced HPE and further widen its application areas. ConvNet-based HPE with its increasingly complex network structures, combined with transfer learning, is a very challenging task. However, the availability of high-performing ImageNet backbones, together with large tailor-made datasets, such as MPII for 2D pose estimation, has facilitated the development of new improved methods to address the challenges. An increasing trend

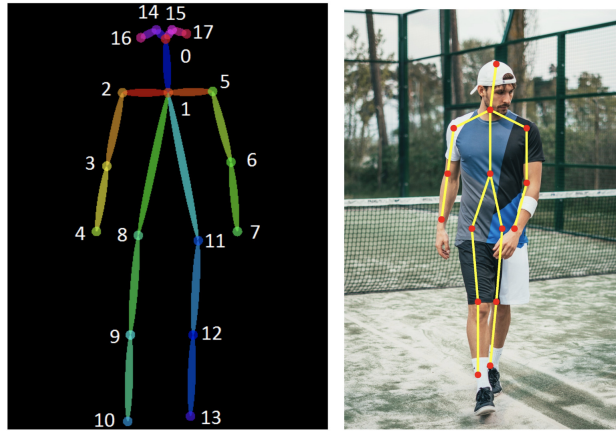


Figure 1.1: Human Pose Estimation Demo

in computer vision has driven towards more efficient models. Recently, EfficientNet was released as a scalable ConvNet architecture, setting benchmark record on ImageNet with a more computationally efficient architecture.

1.2 Problem Statement

Despite the availability of more performant, efficient layers and architecture's, it has not quite translated into fruitful results within human pose estimation, there is still a lack of architectures that are both accurate and computationally efficient

at the same time. In general, current state-of-the-art architectures are computationally expensive and highly complex, thus making them hard to replicate, cumbersome to optimize, and impractical to embed into real-world applications.

Minimal and efficient model architectures are coveted for their ability to run on edge devices with minimal hardware requirements. This also greatly reduces the response times thereby becoming increasingly relevant for real-time applications. The ability to run real-time is a crucial feature for pose estimation, because often times in most applications it's desirable to obtain the outputs instantly to judge the output.

1.3 Objective

Primary objective is to exploit recent advances in ConvNets and shed some light onto an improved approach called EfficientPose. The main idea is to modify OpenPose, a well-known pose estimation model into a family of scalable ConvNets for high-precision and computationally efficient single-person pose estimation from 2D images. Then we evaluate the EfficientPose model by comparing it against the original OpenPose model on single-person HPE. After that, we compare it against the current state-of-the-art single-person HPE methods on the official MPII challenge, focusing on accuracy as a function of the number of parameters. EfficientPose models aim to elicit high computational efficiency, while bridging the gap in availability of high-precision HPE networks.

Chapter 2

Related works

Ever since the increased adoption of ConvNets for HPE following the success of DeepPose has set the path for accurate HPE. Another breakthrough in HPE was provided by OpenPose. OpenPose comprises a multi-stage architecture performing a series of detection passes. Provided an input image of 368×368 pixels, OpenPose utilizes an ImageNet pretrained VGG-19 backbone to extract basic features. The features are supplied to a DenseNet-inspired detection block arranged as five dense blocks, each containing three 3×3 convolutions with PReLU activations. The detection blocks are stacked in a sequence. First, four passes of part affinity fields map the associations between body keypoints. Subsequently, two detection passes predict keypoint heatmaps to obtain refined keypoint coordinate estimates. In terms of level of detail in the keypoint coordinates, OpenPose is restricted by its output resolution of 46×46 pixels. The OpenPose architecture can be improved by recent advancements in ConvNets, as follows: First, automated network architecture search has found backbones that are more precise and efficient in image classification than VGG and ResNets. Compound model scaling can balance the image resolution, width (number of networkchannels), and depth (number of network layers). This resulted in scalable convolutional neural networks, called EfficientNets, with which the main goal was to provide lightweight models with a sensible trade-off between model complexity and accuracy across various computational budgets. For each model variant EfficientNet, from the most computationally efficient one being EfficientNet-B0 to the most accurate model, EfficientNet-B7. The total no. of FLOPS increases by a factor of 2, given by:

$$(\alpha.\beta^2.\gamma^2)^\phi$$

where

$$\alpha = 1.2, \beta = 1.1, \gamma = 1.15$$

They denote the coefficients for depth, width and resolution respectively.

Second, parallel multi-scale feature extraction has improved the precision levels in HPE, emphasizing both high spatial resolution and low-scale semantics. However, existing multi-scale approaches in HPE are computationally expensive, both due to their large size and high computational requirements. For example, a typical multi-scale HPE approach has often a size of 16 to 58 million parameters and requires 10 to 128 GFLOPS. To cope with this, we propose cross-resolution features, operating on high- and low-resolution input images, to integrate features from multiple abstraction levels with low overhead in network complexity and with high computational efficiency. Existing works on Siamese ConvNets have been promising in utilizing parallel network backbones. Third, mobile inverted bottleneck convolution (MBConv) with built-in squeeze-and- excitation (SE) and Swish activation integrated in EfficientNets has proven more accurate in image classification

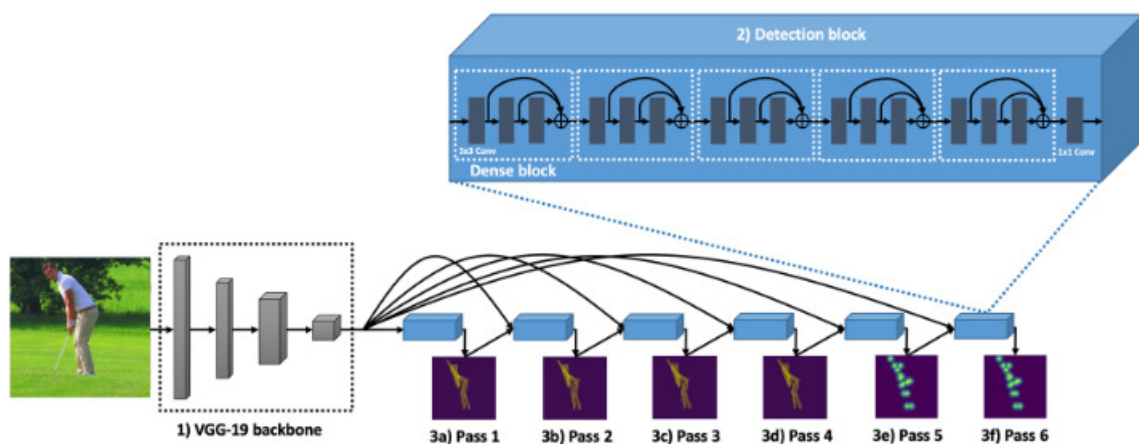


Figure 2.1: OpenPose

tasks than regular convolutions, while substantially reducing the computational costs. The efficiency of MBConv modules stem from the depthwise convolutions operating in a channel-wise manner. With this approach, it is possible to reduce the computational cost by a factor proportional to the number of channels. Hence, by replacing the regular 3×3 convolutions with up to 384 input channels in the detection blocks of OpenPose with MBConvs, we can obtain more computationally efficient detection blocks. Further, SE selectively emphasizes discriminative image features, which may reduce the required number of convolutions and detection passes by providing a global perspective on the estimation task at all times. Using MBConv with SE may have the potential to decrease the number of dense blocks in OpenPose. Fourth, transposed convolutions with bilinear kernel scale up the low-resolution feature maps, thus enabling a higher level of detail in the output confidence maps. The main advantage of this is that we can use ConvNets that are small and computationally efficient enough to run on edge devices with little memory and low processing power, which is impossible with OpenPose. We can also alter the parameters of EfficientNet to obtain different variants with accuracies and efficiencies that are different.

Chapter 3

Design

3.1 Introduction

Here, the model architecture we use, namely EfficientPose exploits the recent advancements in ConvNets and additionally concatenates high-level and low-level features. The net result is a much more efficient model with better accuracy and needing fewer computational resources.

3.2 Architecture

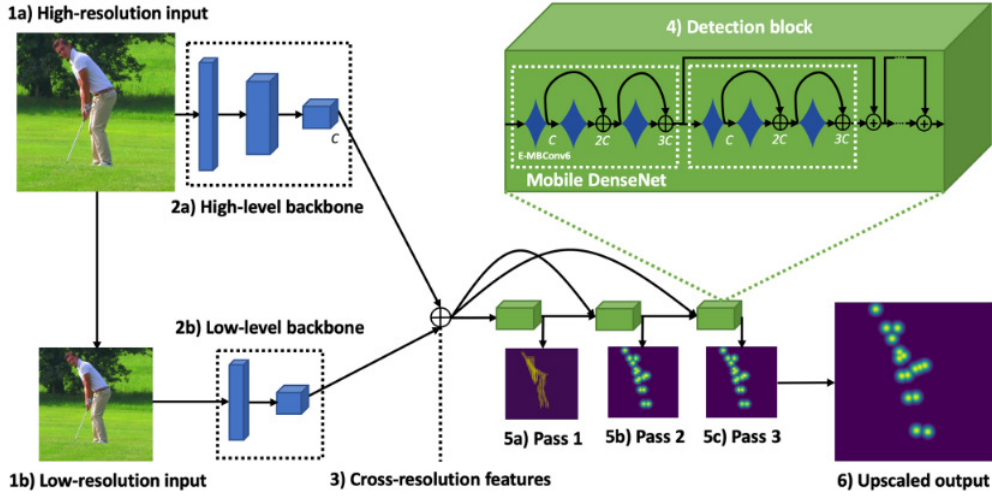


Figure 3.1: EfficientPose

The model takes in two inputs, one is the high-level features and second is the low-level features. The low level features are obtained by downsampling an image to half of it's height and width using an average pooling layer. The feature extractors here are initial layers of EfficientNet. For high level extractor, $\phi \in [0, 7]$ and for the low level extractor $\phi \in [0, 3]$.

These extracted features are then concatenated together to obtain cross-resolution features. This helps us to emphasize the important local factors in the image of interest.

The input to the next phase of the model is the cross-resolution features obtained in the previous step. Here the required keypoints are localized through

an iterative process, where each detection pass performs supervised prediction of output maps. Each detection pass comprises a detection block and a single 1×1 convolution for output prediction. The detection blocks across all detection passes exhibit the same basic architecture, comprising Mobile DenseNets. Data from here is forwarded to the successive layers through skip connections. Here, we also avoid downsampling of the output to preserve the resolution. The original mobile convnets are modified by adding an E-swish activation function with β value 1.25.

The overall detection is performed in two rounds. Initially, the overall pose of the person is anticipated through a single pass of skeleton estimation. This helps especially when there are multiple people present in the frame. After the skeleton estimation is done two detection passes are performed to estimate heatmaps for points of interest.

Another improvement on top of OpenPose is that, EfficientPose projects lower-resolution image onto a higher resolution space using transposed convolution to allow an increased level of detail, whereas in OpenPose the heatmaps are constrained to the lower space.

3.3 Modules

3.3.1 EfficientNet

In mathematics, Stirling's approximation (or Stirling's formula) is an approximation for large factorials. It is named after James Stirling.

3.3.2 E-Swish

3.4 Accuracy Measures

Chapter 4

Datasets

4.1 MPII Human Pose Dataset

MPII Human Pose dataset is a state of the art benchmark for evaluation of articulated human pose estimation. The dataset includes around 25K images containing over 40K people with annotated body joints. The images were systematically collected using an established taxonomy of every day human activities. Overall the dataset covers 410 human activities and each image is provided with an activity label. Each image was extracted from a YouTube video and provided with preceding and following un-annotated frames. In addition, for the test set we obtained richer annotations including body part occlusions and 3D torso and head orientations. The model was trained primarily on this dataset.

4.2 Leeds Sports Dataset

This dataset contains 2000 pose annotated images of mostly sports people gathered from Flickr using the tags shown above. The images have been scaled such that the most prominent person is roughly 150 pixels in length. Each image has been annotated with 14 joint locations. Left and right joints are consistently labelled from a person-centric viewpoint. Attributions and Flickr URLs for the original images can be found in the JPEG comment field of each image file. The ordering of the joints are as follows:

1. Right Ankle
2. Right Knew
3. Right Hip
4. Left Hip
5. Left Knee
6. Left Ankle
7. Right Wrist
8. Right Elbow
9. Right Shoulder
10. Left Shoulder

11. Left Elbow
12. Left Wrist
13. Neck
14. Head Top

Chapter 5

Results

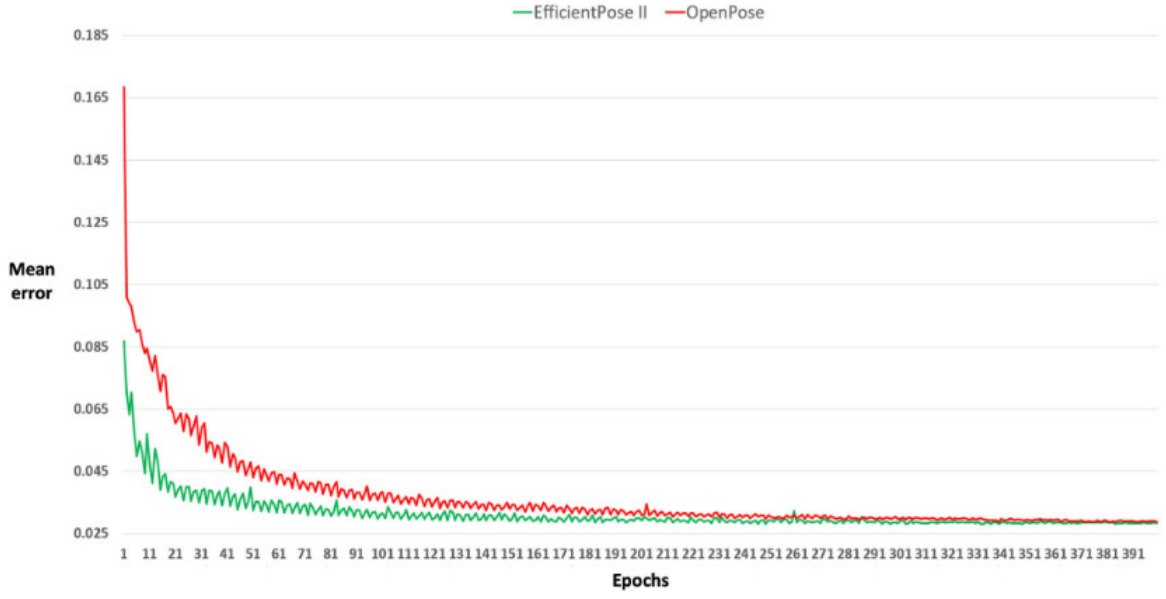


Figure 5.1: Convergence of mean error on OpenPose and EfficientPose

Some text

Table 5.1: Comparison of EfficientPose and OpenPose on MPII validation dataset

Model	Parameters	Parameter Reduction	FLOPs	FLOP Reduction	$PCK_h@50$	$PCK_h@50$
1	China	1,347,350,000	19.24%			
2	India	1,210,193,422	17.28%			
3	United States	313,269,000	4.47%			

Chapter 6

Outputs



Figure 6.1: Output 1

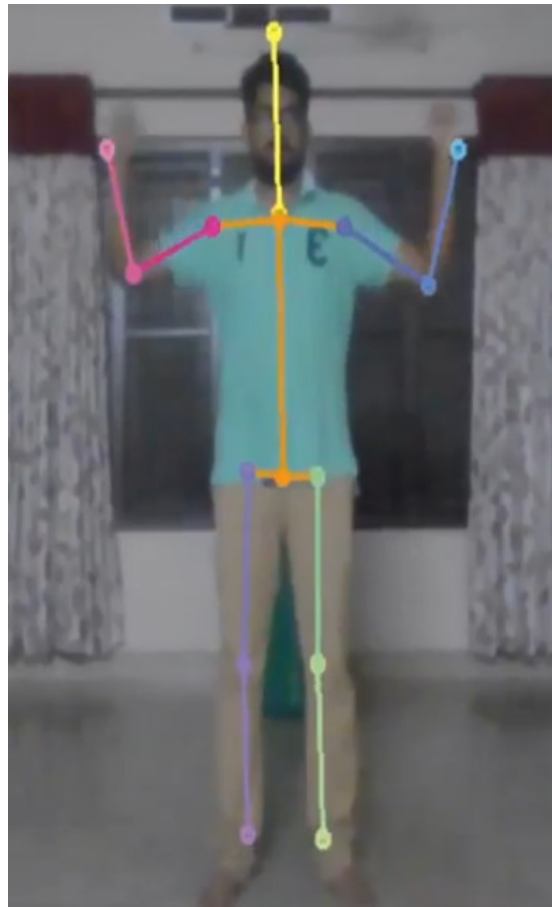


Figure 6.2: Output 2

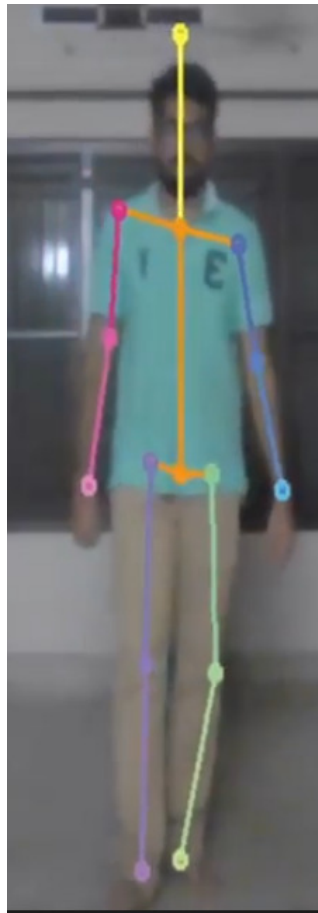


Figure 6.3: Output 3

Chapter 7

Conclusion

By successfully exploiting the recent advances in convolutional neural networks, we have successfully made Single Person Pose-Estimation both more efficient and more accurate. Due to this, many avenues of products in different fields may be developed that require real time pose estimation and hopefully it can be used for wide ranging applications and products. The main advantage is the ability to run on edge devices which has been an achillies heal of HPE for a long time.

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Appendices

.1 Source Code of EfficientPoseRT

```
class KitModel(nn.Module):
```

```
    def __init__(self, weight_file):
        super(KitModel, self).__init__()
        global __weights_dict
        __weights_dict = load_weights(weight_file)

        self.stem_conv_res1_convolution = self.__conv(2, name='stem_conv
        self.stem_bn_res1_FusedBatchNorm_1 = self.__batch_normalization(
        self.block1a_dwconv_res1_depthwise = self.__conv(2, name='block1
        self.block1a_bn_res1_FusedBatchNorm_1 = self.__batch_normalization
        self.block1a_se_reduce_res1_convolution = self.__conv(2, name='b
        self.block1a_se_expand_res1_convolution = self.__conv(2, name='b
        self.block1a_project_conv_res1_convolution = self.__conv(2, name
        self.block1a_project_bn_res1_FusedBatchNorm_1 = self.__batch_nor
        self.block2a_expand_conv_res1_convolution = self.__conv(2, name=
        self.block2a_expand_bn_res1_FusedBatchNorm_1 = self.__batch_norm
        self.block2a_dwconv_res1_depthwise = self.__conv(2, name='block2
        self.block2a_bn_res1_FusedBatchNorm_1 = self.__batch_normalization
        self.block2a_se_reduce_res1_convolution = self.__conv(2, name='b
        self.block2a_se_expand_res1_convolution = self.__conv(2, name='b
        self.block2a_project_conv_res1_convolution = self.__conv(2, name
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        self.block3a_project_conv_res1_convolution = self.__conv(2, name
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        self.block3b_expand_conv_res1_convolution = self.__conv(2, name=
        self.block3b_expand_bn_res1_FusedBatchNorm_1 = self.__batch_norm
        self.block3b_dwconv_res1_depthwise = self.__conv(2, name='block3
        self.block3b_bn_res1_FusedBatchNorm_1 = self.__batch_normalization
        self.block3b_se_reduce_res1_convolution = self.__conv(2, name='b
        self.block3b_se_expand_res1_convolution = self.__conv(2, name='b
        self.block3b_project_conv_res1_convolution = self.__conv(2, name
```



```
self.block3b_project_bn_res1_FusedBatchNorm_1 = self._batch_norm
self.pass1_block1_mbconv1_skeleton_conv1_convolution = self._conv2d
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self.pass3_detection2_confs_convolution = self.__conv(2, name='p

def forward(self, x):
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self.pass1_block1_mbconv2_skeleton_se_se_squeeze_eswish_mul_x =
self.pass1_block1_mbconv3_skeleton_conv1_eswish_mul_x = torch.au
self.pass1_block1_mbconv3_skeleton_dconv1_eswish_mul_x = torch.a
self.pass1_block1_mbconv3_skeleton_se_se_squeeze_eswish_mul_x =
self.pass2_block1_mbconv1_detection1_conv1_eswish_mul_x = torch
self.pass2_block1_mbconv1_detection1_dconv1_eswish_mul_x = torch
self.pass2_block1_mbconv1_detection1_se_se_squeeze_eswish_mul_x =
self.pass2_block1_mbconv2_detection1_conv1_eswish_mul_x = torch.
self.pass2_block1_mbconv2_detection1_dconv1_eswish_mul_x = torch
self.pass2_block1_mbconv2_detection1_se_se_squeeze_eswish_mul_x =
self.pass2_block1_mbconv3_detection1_conv1_eswish_mul_x = torch.
self.pass2_block1_mbconv3_detection1_dconv1_eswish_mul_x = torch
self.pass2_block1_mbconv3_detection1_se_se_squeeze_eswish_mul_x =
self.pass3_block1_mbconv1_detection2_conv1_eswish_mul_x = torch.
self.pass3_block1_mbconv1_detection2_dconv1_eswish_mul_x = torch
self.pass3_block1_mbconv1_detection2_se_se_squeeze_eswish_mul_x =
self.pass3_block1_mbconv2_detection2_conv1_eswish_mul_x = torch.
self.pass3_block1_mbconv2_detection2_dconv1_eswish_mul_x = torch
self.pass3_block1_mbconv2_detection2_se_se_squeeze_eswish_mul_x =
```

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self.pass3_block1_mbconv3_detection2_conv1_eswish_mul_x = torch.  
self.pass3_block1_mbconv3_detection2_dconv1_eswish_mul_x = torch.  
self.pass3_block1_mbconv3_detection2_se_se_squeeze_eswish_mul_x :  
stem_conv_res1_convolution_pad = F.pad(x, (0, 1, 0, 1))  
stem_conv_res1_convolution = self.stem_conv_res1_convolution(stem.  
stem_bn_res1_FusedBatchNorm_1 = self.stem_bn_res1_FusedBatchNorm  
stem_activation_res1_Sigmoid = F.sigmoid(stem_bn_res1_FusedBatchM  
stem_activation_res1_mul = stem_bn_res1_FusedBatchNorm_1 * stem.  
block1a_dwconv_res1_depthwise_pad = F.pad(stem_activation_res1_m  
block1a_dwconv_res1_depthwise = self.block1a_dwconv_res1_depthwi  
block1a_bn_res1_FusedBatchNorm_1 = self.block1a_bn_res1_FusedBato  
block1a_activation_res1_Sigmoid = F.sigmoid(block1a_bn_res1_Fused  
block1a_activation_res1_mul = block1a_bn_res1_FusedBatchNorm_1 *  
block1a_se_squeeze_res1_Mean = torch.mean(block1a_activation_res1  
block1a_se_squeeze_res1_Mean = torch.mean(block1a_se_squeeze_res1  
block1a_se_reshape_res1_Shape = torch.Tensor(list(block1a_se_squ  
block1a_se_reshape_res1_Reshape = torch.reshape(input = block1a.  
block1a_se_reshape_res1_strided_slice = block1a_se_reshape_res1_S  
block1a_se_reduce_res1_convolution = self.block1a_se_reduce_res1  
block1a_se_reduce_swish_res1_Sigmoid = F.sigmoid(block1a_se_redu  
block1a_se_reduce_swish_res1_mul = block1a_se_reduce_res1_convol  
block1a_se_expand_res1_convolution = self.block1a_se_expand_res1  
block1a_se_expand_res1_Sigmoid = F.sigmoid(block1a_se_expand_res  
block1a_se_excite_res1_mul = block1a_activation_res1_mul * block  
block1a_project_conv_res1_convolution = self.block1a_project_con  
block1a_project_bn_res1_FusedBatchNorm_1 = self.block1a_project_b  
block2a_expand_conv_res1_convolution = self.block2a_expand_conv.  
block2a_expand_bn_res1_FusedBatchNorm_1 = self.block2a_expand_bn  
block2a_expand_activation_res1_Sigmoid = F.sigmoid(block2a_expan  
block2a_expand_activation_res1_mul = block2a_expand_bn_res1_Fused  
block2a_dwconv_res1_depthwise_pad = F.pad(block2a_expand_activat  
block2a_dwconv_res1_depthwise = self.block2a_dwconv_res1_depthwi  
block2a_bn_res1_FusedBatchNorm_1 = self.block2a_bn_res1_FusedBato  
block2a_activation_res1_Sigmoid = F.sigmoid(block2a_bn_res1_Fused  
block2a_activation_res1_mul = block2a_bn_res1_FusedBatchNorm_1 *  
block2a_se_squeeze_res1_Mean = torch.mean(block2a_activation_res1  
block2a_se_squeeze_res1_Mean = torch.mean(block2a_se_squeeze_res1  
block2a_se_reshape_res1_Shape = torch.Tensor(list(block2a_se_squ  
block2a_se_reshape_res1_Reshape = torch.reshape(input = block2a.  
block2a_se_reshape_res1_strided_slice = block2a_se_reshape_res1_S  
block2a_se_reduce_res1_convolution = self.block2a_se_reduce_res1  
block2a_se_reduce_swish_res1_Sigmoid = F.sigmoid(block2a_se_redu  
block2a_se_reduce_swish_res1_mul = block2a_se_reduce_res1_convol  
block2a_se_expand_res1_convolution = self.block2a_se_expand_res1  
block2a_se_expand_res1_Sigmoid = F.sigmoid(block2a_se_expand_res  
block2a_se_excite_res1_mul = block2a_activation_res1_mul * block  
block2a_project_conv_res1_convolution = self.block2a_project_con  
block2a_project_bn_res1_FusedBatchNorm_1 = self.block2a_project_b  
block2b_expand_conv_res1_convolution = self.block2b_expand_conv.  
block2b_expand_bn_res1_FusedBatchNorm_1 = self.block2b_expand_bn
```

```
block2b_expand_activation_res1_Sigmoid = F.sigmoid(block2b_expand_activation_res1_mul)
block2b_expand_activation_res1_mul = block2b_expand_bn_res1_FusedBatchNorm_1 * block2b_expand_activation_res1_Sigmoid
block2b_dwconv_res1_depthwise_pad = F.pad(block2b_expand_activation_res1_mul, [1, 1, 1, 1])
block2b_dwconv_res1_depthwise = self.block2b_dwconv_res1_depthwise
block2b_bn_res1_FusedBatchNorm_1 = self.block2b_bn_res1_FusedBatchNorm_1
block2b_activation_res1_Sigmoid = F.sigmoid(block2b_bn_res1_FusedBatchNorm_1 * block2b_dwconv_res1_depthwise)
block2b_activation_res1_mul = block2b_bn_res1_FusedBatchNorm_1 * block2b_activation_res1_Sigmoid
block2b_se_squeeze_res1_Mean = torch.mean(block2b_activation_res1_mul, [1, 2, 3])
block2b_se_squeeze_res1_Mean = torch.mean(block2b_se_squeeze_res1_Mean, [1, 2, 3])
block2b_se_reshape_res1_Shape = torch.Tensor(list(block2b_se_squeeze_res1_Mean.shape))
block2b_se_reshape_res1_Reshape = torch.reshape(input = block2b_activation_res1_mul, [1, 1, 1, 1])
block2b_se_reshape_res1_strided_slice = block2b_se_reshape_res1_Reshape
block2b_se_reduce_res1_convolution = self.block2b_se_reduce_res1_convolution
block2b_se_reduce_swish_res1_Sigmoid = F.sigmoid(block2b_se_reduce_res1_convolution)
block2b_se_reduce_swish_res1_mul = block2b_se_reduce_res1_convolution * block2b_se_reduce_swish_res1_Sigmoid
block2b_se_expand_res1_convolution = self.block2b_se_expand_res1_convolution
block2b_se_expand_res1_Sigmoid = F.sigmoid(block2b_se_expand_res1_convolution)
block2b_se_excite_res1_mul = block2b_activation_res1_mul * block2b_se_expand_res1_Sigmoid
block2b_project_conv_res1_convolution = self.block2b_project_conv_res1_convolution
block2b_project_bn_res1_FusedBatchNorm_1 = self.block2b_project_bn_res1_FusedBatchNorm_1
block2b_add_res1_add = block2b_project_bn_res1_FusedBatchNorm_1 + block2b_se_excite_res1_mul
block3a_expand_conv_res1_convolution = self.block3a_expand_conv_res1_convolution
block3a_expand_bn_res1_FusedBatchNorm_1 = self.block3a_expand_bn_res1_FusedBatchNorm_1
block3a_expand_activation_res1_Sigmoid = F.sigmoid(block3a_expand_bn_res1_FusedBatchNorm_1 * block3a_expand_conv_res1_convolution)
block3a_expand_activation_res1_mul = block3a_expand_bn_res1_FusedBatchNorm_1 * block3a_expand_activation_res1_Sigmoid
block3a_dwconv_res1_depthwise_pad = F.pad(block3a_expand_activation_res1_mul, [1, 1, 1, 1])
block3a_dwconv_res1_depthwise = self.block3a_dwconv_res1_depthwise
block3a_bn_res1_FusedBatchNorm_1 = self.block3a_bn_res1_FusedBatchNorm_1
block3a_activation_res1_Sigmoid = F.sigmoid(block3a_bn_res1_FusedBatchNorm_1 * block3a_dwconv_res1_depthwise)
block3a_activation_res1_mul = block3a_bn_res1_FusedBatchNorm_1 * block3a_activation_res1_Sigmoid
block3a_se_squeeze_res1_Mean = torch.mean(block3a_activation_res1_mul, [1, 2, 3])
block3a_se_squeeze_res1_Mean = torch.mean(block3a_se_squeeze_res1_Mean, [1, 2, 3])
block3a_se_reshape_res1_Shape = torch.Tensor(list(block3a_se_squeeze_res1_Mean.shape))
block3a_se_reshape_res1_Reshape = torch.reshape(input = block3a_activation_res1_mul, [1, 1, 1, 1])
block3a_se_reshape_res1_strided_slice = block3a_se_reshape_res1_Reshape
block3a_se_reduce_res1_convolution = self.block3a_se_reduce_res1_convolution
block3a_se_reduce_swish_res1_Sigmoid = F.sigmoid(block3a_se_reduce_res1_convolution)
block3a_se_reduce_swish_res1_mul = block3a_se_reduce_res1_convolution * block3a_se_reduce_swish_res1_Sigmoid
block3a_se_expand_res1_convolution = self.block3a_se_expand_res1_convolution
block3a_se_expand_res1_Sigmoid = F.sigmoid(block3a_se_expand_res1_convolution)
block3a_se_excite_res1_mul = block3a_activation_res1_mul * block3a_se_expand_res1_Sigmoid
block3a_project_conv_res1_convolution = self.block3a_project_conv_res1_convolution
block3a_project_bn_res1_FusedBatchNorm_1 = self.block3a_project_bn_res1_FusedBatchNorm_1
block3b_expand_conv_res1_convolution = self.block3b_expand_conv_res1_convolution
block3b_expand_bn_res1_FusedBatchNorm_1 = self.block3b_expand_bn_res1_FusedBatchNorm_1
block3b_expand_activation_res1_Sigmoid = F.sigmoid(block3b_expand_bn_res1_FusedBatchNorm_1 * block3b_expand_conv_res1_convolution)
block3b_expand_activation_res1_mul = block3b_expand_bn_res1_FusedBatchNorm_1 * block3b_expand_activation_res1_Sigmoid
block3b_dwconv_res1_depthwise_pad = F.pad(block3b_expand_activation_res1_mul, [1, 1, 1, 1])
block3b_dwconv_res1_depthwise = self.block3b_dwconv_res1_depthwise
block3b_bn_res1_FusedBatchNorm_1 = self.block3b_bn_res1_FusedBatchNorm_1
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block3b_activation_res1_Sigmoid = F.sigmoid(block3b_bn_res1_FusedBatchNorm_1 *
block3b_activation_res1_mul = block3b_bn_res1_FusedBatchNorm_1 *
block3b_se_squeeze_res1_Mean = torch.mean(block3b_activation_res1_mul, dim=[1, 2, 3])
block3b_se_squeeze_res1_Mean = torch.mean(block3b_se_squeeze_res1_Mean, dim=[1, 2, 3])
block3b_se_reshape_res1_Shape = torch.Tensor(list(block3b_se_squeeze_res1_Mean.shape[1:]))
block3b_se_reshape_res1_Reshape = torch.reshape(input = block3b_activation_res1_mul,
block3b_se_reshape_res1_strided_slice = block3b_se_reshape_res1_Reshape *
block3b_se_reduce_res1_convolution = self.block3b_se_reduce_res1_convolution
block3b_se_reduce_swish_res1_Sigmoid = F.sigmoid(block3b_se_reduce_res1_convolution)
block3b_se_reduce_swish_res1_mul = block3b_se_reduce_res1_convolution *
block3b_se_expand_res1_convolution = self.block3b_se_expand_res1_convolution
block3b_se_expand_res1_Sigmoid = F.sigmoid(block3b_se_expand_res1_convolution)
block3b_se_excite_res1_mul = block3b_activation_res1_mul *
block3b_project_conv_res1_convolution = self.block3b_project_conv_res1_convolution
block3b_project_bn_res1_FusedBatchNorm_1 = self.block3b_project_bn_res1_FusedBatchNorm_1
block3b_add_res1_add = block3b_project_bn_res1_FusedBatchNorm_1 +
pass1_block1_mbconv1_skeleton_conv1_convolution = self.pass1_block1_mbconv1_skeleton_conv1_convolution
pass1_block1_mbconv1_skeleton_conv1_bn_FusedBatchNorm_1 = self.pass1_block1_mbconv1_skeleton_conv1_bn_FusedBatchNorm_1
pass1_block1_mbconv1_skeleton_conv1_eswish_mul = self.pass1_block1_mbconv1_skeleton_conv1_eswish_mul
pass1_block1_mbconv1_skeleton_conv1_eswish_Sigmoid = F.sigmoid(pass1_block1_mbconv1_skeleton_conv1_eswish_mul)
pass1_block1_mbconv1_skeleton_conv1_eswish_mul_1 = pass1_block1_mbconv1_skeleton_conv1_eswish_mul *
pass1_block1_mbconv1_skeleton_dconv1_depthwise_pad = F.pad(pass1_block1_mbconv1_skeleton_conv1_eswish_mul_1,
pass1_block1_mbconv1_skeleton_dconv1_depthwise = self.pass1_block1_mbconv1_skeleton_dconv1_depthwise
pass1_block1_mbconv1_skeleton_dconv1_bn_FusedBatchNorm_1 = self.pass1_block1_mbconv1_skeleton_dconv1_bn_FusedBatchNorm_1
pass1_block1_mbconv1_skeleton_dconv1_eswish_mul = self.pass1_block1_mbconv1_skeleton_dconv1_eswish_mul
pass1_block1_mbconv1_skeleton_dconv1_eswish_Sigmoid = F.sigmoid(pass1_block1_mbconv1_skeleton_dconv1_eswish_mul)
pass1_block1_mbconv1_skeleton_dconv1_eswish_mul_1 = pass1_block1_mbconv1_skeleton_dconv1_eswish_mul *
pass1_block1_mbconv1_skeleton_se_se_squeeze_lambda_Mean = torch.mean(pass1_block1_mbconv1_skeleton_dconv1_eswish_mul_1, dim=[1, 2, 3])
pass1_block1_mbconv1_skeleton_se_se_squeeze_lambda_Mean = torch.mean(pass1_block1_mbconv1_skeleton_se_se_squeeze_lambda_Mean, dim=[1, 2, 3])
pass1_block1_mbconv1_skeleton_se_se_squeeze_conv_convolution = self.pass1_block1_mbconv1_skeleton_se_se_squeeze_conv_convolution
pass1_block1_mbconv1_skeleton_se_se_squeeze_eswish_mul = self.pass1_block1_mbconv1_skeleton_se_se_squeeze_conv_convolution
pass1_block1_mbconv1_skeleton_se_se_squeeze_eswish_Sigmoid = F.sigmoid(pass1_block1_mbconv1_skeleton_se_se_squeeze_eswish_mul)
pass1_block1_mbconv1_skeleton_se_se_squeeze_eswish_mul_1 = pass1_block1_mbconv1_skeleton_se_se_squeeze_eswish_mul *
pass1_block1_mbconv1_skeleton_se_se_excite_conv_convolution = self.pass1_block1_mbconv1_skeleton_se_se_excite_conv_convolution
pass1_block1_mbconv1_skeleton_se_se_excite_sigmoid_Sigmoid = F.sigmoid(pass1_block1_mbconv1_skeleton_se_se_excite_conv_convolution)
pass1_block1_mbconv1_skeleton_se_se_multiply_mul = pass1_block1_mbconv1_skeleton_se_se_excite_sigmoid_Sigmoid *
pass1_block1_mbconv1_skeleton_conv2_convolution = self.pass1_block1_mbconv1_skeleton_conv2_convolution
pass1_block1_mbconv1_skeleton_conv2_bn_FusedBatchNorm_1 = self.pass1_block1_mbconv1_skeleton_conv2_bn_FusedBatchNorm_1
pass1_block1_mbconv2_skeleton_conv1_convolution = self.pass1_block1_mbconv2_skeleton_conv1_convolution
pass1_block1_mbconv2_skeleton_conv1_bn_FusedBatchNorm_1 = self.pass1_block1_mbconv2_skeleton_conv1_bn_FusedBatchNorm_1
pass1_block1_mbconv2_skeleton_conv1_eswish_mul = self.pass1_block1_mbconv2_skeleton_conv1_eswish_mul
pass1_block1_mbconv2_skeleton_conv1_eswish_Sigmoid = F.sigmoid(pass1_block1_mbconv2_skeleton_conv1_eswish_mul)
pass1_block1_mbconv2_skeleton_conv1_eswish_mul_1 = pass1_block1_mbconv2_skeleton_conv1_eswish_mul *
pass1_block1_mbconv2_skeleton_dconv1_depthwise_pad = F.pad(pass1_block1_mbconv2_skeleton_conv1_eswish_mul_1,
pass1_block1_mbconv2_skeleton_dconv1_depthwise = self.pass1_block1_mbconv2_skeleton_dconv1_depthwise
pass1_block1_mbconv2_skeleton_dconv1_bn_FusedBatchNorm_1 = self.pass1_block1_mbconv2_skeleton_dconv1_bn_FusedBatchNorm_1
pass1_block1_mbconv2_skeleton_dconv1_eswish_mul = self.pass1_block1_mbconv2_skeleton_dconv1_eswish_mul
pass1_block1_mbconv2_skeleton_dconv1_eswish_Sigmoid = F.sigmoid(pass1_block1_mbconv2_skeleton_dconv1_eswish_mul)
pass1_block1_mbconv2_skeleton_dconv1_eswish_mul_1 = pass1_block1_mbconv2_skeleton_dconv1_eswish_mul *
pass1_block1_mbconv2_skeleton_se_se_squeeze_lambda_Mean = torch.mean(pass1_block1_mbconv2_skeleton_dconv1_eswish_mul_1, dim=[1, 2, 3])
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pass1_block1_mbconv2_skeleton_se_se_squeeze_lambda_Mean = torch.
pass1_block1_mbconv2_skeleton_se_se_squeeze_conv_convolution = s
pass1_block1_mbconv2_skeleton_se_se_squeeze_eswish_mul = self.pa
pass1_block1_mbconv2_skeleton_se_se_squeeze_eswish_Sigmoid = F.s
pass1_block1_mbconv2_skeleton_se_se_squeeze_eswish_mul_1 = pass1
pass1_block1_mbconv2_skeleton_se_se_excite_conv_convolution = se
pass1_block1_mbconv2_skeleton_se_se_excite_sigmoid_Sigmoid = F.s
pass1_block1_mbconv2_skeleton_se_se_multiply_mul = pass1_block1
pass1_block1_mbconv2_skeleton_conv2_convolution = self.pass1_blo
pass1_block1_mbconv2_skeleton_conv2_bn_FusedBatchNorm_1 = self.p
pass1_block1_mbconv2_skeleton_dense_concat = torch.cat((pass1_blo
pass1_block1_mbconv3_skeleton_conv1_convolution = self.pass1_blo
pass1_block1_mbconv3_skeleton_conv1_bn_FusedBatchNorm_1 = self.p
pass1_block1_mbconv3_skeleton_conv1_eswish_mul = self.pass1_blo
pass1_block1_mbconv3_skeleton_conv1_eswish_Sigmoid = F.sigmoid(p
pass1_block1_mbconv3_skeleton_conv1_eswish_mul_1 = pass1_block1_r
pass1_block1_mbconv3_skeleton_dconv1_depthwise_pad = F.pad(pass1
pass1_block1_mbconv3_skeleton_dconv1_depthwise = self.pass1_blo
pass1_block1_mbconv3_skeleton_dconv1_bn_FusedBatchNorm_1 = self.
pass1_block1_mbconv3_skeleton_dconv1_eswish_mul = self.pass1_blo
pass1_block1_mbconv3_skeleton_dconv1_eswish_Sigmoid = F.sigmoid(
pass1_block1_mbconv3_skeleton_dconv1_eswish_mul_1 = pass1_block1
pass1_block1_mbconv3_skeleton_se_se_squeeze_lambda_Mean = torch.
pass1_block1_mbconv3_skeleton_se_se_squeeze_lambda_Mean = torch.
pass1_block1_mbconv3_skeleton_se_se_squeeze_conv_convolution = s
pass1_block1_mbconv3_skeleton_se_se_squeeze_eswish_mul = self.pa
pass1_block1_mbconv3_skeleton_se_se_squeeze_eswish_Sigmoid = F.s
pass1_block1_mbconv3_skeleton_se_se_squeeze_eswish_mul_1 = pass1
pass1_block1_mbconv3_skeleton_se_se_excite_conv_convolution = se
pass1_block1_mbconv3_skeleton_se_se_excite_sigmoid_Sigmoid = F.s
pass1_block1_mbconv3_skeleton_se_se_multiply_mul = pass1_block1
pass1_block1_mbconv3_skeleton_conv2_convolution = self.pass1_blo
pass1_block1_mbconv3_skeleton_conv2_bn_FusedBatchNorm_1 = self.p
pass1_block1_mbconv3_skeleton_dense_concat = torch.cat((pass1_blo
concatenate_1_concat = torch.cat((pass1_block1_mbconv3_skeleton
pass2_block1_mbconv1_detection1_conv1_convolution = self.pass2_b
pass2_block1_mbconv1_detection1_conv1_bn_FusedBatchNorm_1 = self
pass2_block1_mbconv1_detection1_conv1_eswish_mul = self.pass2_blo
pass2_block1_mbconv1_detection1_conv1_eswish_Sigmoid = F.sigmoid
pass2_block1_mbconv1_detection1_conv1_eswish_mul_1 = pass2_block
pass2_block1_mbconv1_detection1_dconv1_depthwise_pad = F.pad(pas
pass2_block1_mbconv1_detection1_dconv1_depthwise = self.pass2_blo
pass2_block1_mbconv1_detection1_dconv1_bn_FusedBatchNorm_1 = sel
pass2_block1_mbconv1_detection1_dconv1_eswish_mul = self.pass2_b
pass2_block1_mbconv1_detection1_dconv1_eswish_Sigmoid = F.sigmoi
pass2_block1_mbconv1_detection1_dconv1_eswish_mul_1 = pass2_blo
pass2_block1_mbconv1_detection1_se_se_squeeze_lambda_Mean = torc
pass2_block1_mbconv1_detection1_se_se_squeeze_lambda_Mean = torc
pass2_block1_mbconv1_detection1_se_se_squeeze_conv_convolution =
pass2_block1_mbconv1_detection1_se_se_squeeze_eswish_mul = self.
```

```
pass2_block1_mbconv1_detection1_se_se_squeeze_eswish_Sigmoid = F
pass2_block1_mbconv1_detection1_se_se_squeeze_eswish_mul_1 = pas
pass2_block1_mbconv1_detection1_se_se_excite_conv_convolution =
pass2_block1_mbconv1_detection1_se_se_excite_sigmoid_Sigmoid = F
pass2_block1_mbconv1_detection1_se_se_multiply_mul = pass2_block
pass2_block1_mbconv1_detection1_conv2_convolution = self.pass2_b
pass2_block1_mbconv1_detection1_conv2_bn_FusedBatchNorm_1 = self
pass2_block1_mbconv2_detection1_conv1_convolution = self.pass2_b
pass2_block1_mbconv2_detection1_conv1_bn_FusedBatchNorm_1 = self
pass2_block1_mbconv2_detection1_conv1_eswish_mul = self.pass2_bl
pass2_block1_mbconv2_detection1_conv1_eswish_Sigmoid = F.sigmoid
pass2_block1_mbconv2_detection1_conv1_eswish_mul_1 = pass2_block
pass2_block1_mbconv2_detection1_dconv1_depthwise_pad = F.pad(pas
pass2_block1_mbconv2_detection1_dconv1_depthwise = self.pass2_bl
pass2_block1_mbconv2_detection1_dconv1_bn_FusedBatchNorm_1 = sel
pass2_block1_mbconv2_detection1_dconv1_eswish_mul = self.pass2_b
pass2_block1_mbconv2_detection1_dconv1_eswish_Sigmoid = F.sigmoi
pass2_block1_mbconv2_detection1_dconv1_eswish_mul_1 = pass2_block
pass2_block1_mbconv2_detection1_se_se_squeeze_lambda_Mean = torch
pass2_block1_mbconv2_detection1_se_se_squeeze_lambda_Mean = torch
pass2_block1_mbconv2_detection1_se_se_squeeze_conv_convolution =
pass2_block1_mbconv2_detection1_se_se_squeeze_eswish_mul = self.
pass2_block1_mbconv2_detection1_se_se_squeeze_eswish_Sigmoid = F
pass2_block1_mbconv2_detection1_se_se_squeeze_eswish_mul_1 = pas
pass2_block1_mbconv2_detection1_se_se_excite_conv_convolution =
pass2_block1_mbconv2_detection1_se_se_excite_sigmoid_Sigmoid = F
pass2_block1_mbconv2_detection1_se_se_multiply_mul = pass2_block
pass2_block1_mbconv2_detection1_conv2_convolution = self.pass2_b
pass2_block1_mbconv2_detection1_conv2_bn_FusedBatchNorm_1 = self
pass2_block1_mbconv2_detection1_dense_concat = torch.cat((pass2.l
pass2_block1_mbconv3_detection1_conv1_convolution = self.pass2_b
pass2_block1_mbconv3_detection1_conv1_bn_FusedBatchNorm_1 = self
pass2_block1_mbconv3_detection1_conv1_eswish_mul = self.pass2_bl
pass2_block1_mbconv3_detection1_conv1_eswish_Sigmoid = F.sigmoid
pass2_block1_mbconv3_detection1_conv1_eswish_mul_1 = pass2_block
pass2_block1_mbconv3_detection1_dconv1_depthwise_pad = F.pad(pas
pass2_block1_mbconv3_detection1_dconv1_depthwise = self.pass2_bl
pass2_block1_mbconv3_detection1_dconv1_bn_FusedBatchNorm_1 = sel
pass2_block1_mbconv3_detection1_dconv1_eswish_mul = self.pass2_b
pass2_block1_mbconv3_detection1_dconv1_eswish_Sigmoid = F.sigmoi
pass2_block1_mbconv3_detection1_dconv1_eswish_mul_1 = pass2_block
pass2_block1_mbconv3_detection1_se_se_squeeze_lambda_Mean = torch
pass2_block1_mbconv3_detection1_se_se_squeeze_lambda_Mean = torch
pass2_block1_mbconv3_detection1_se_se_squeeze_conv_convolution =
pass2_block1_mbconv3_detection1_se_se_squeeze_eswish_mul = self.
pass2_block1_mbconv3_detection1_se_se_squeeze_eswish_Sigmoid = F
pass2_block1_mbconv3_detection1_se_se_squeeze_eswish_mul_1 = pas
pass2_block1_mbconv3_detection1_se_se_excite_conv_convolution =
pass2_block1_mbconv3_detection1_se_se_excite_sigmoid_Sigmoid = F
pass2_block1_mbconv3_detection1_se_se_multiply_mul = pass2_block
```



```
pass3_block1_mbconv3_detection2_conv1_bn_FusedBatchNorm_1 = self
pass3_block1_mbconv3_detection2_conv1_eswish_mul = self.pass3_block1_mbconv3_detection2_conv1_eswish_mul
pass3_block1_mbconv3_detection2_conv1_eswish_Sigmoid = F.sigmoid
pass3_block1_mbconv3_detection2_conv1_eswish_mul_1 = pass3_block1_mbconv3_detection2_conv1_eswish_mul
pass3_block1_mbconv3_detection2_dconv1_depthwise_pad = F.pad(pass3_block1_mbconv3_detection2_conv1_eswish_mul, [1, 1, 1, 1])
pass3_block1_mbconv3_detection2_dconv1_depthwise = self.pass3_block1_mbconv3_detection2_dconv1_depthwise
pass3_block1_mbconv3_detection2_dconv1_bn_FusedBatchNorm_1 = self
pass3_block1_mbconv3_detection2_dconv1_eswish_mul = self.pass3_block1_mbconv3_detection2_dconv1_eswish_mul
pass3_block1_mbconv3_detection2_dconv1_eswish_Sigmoid = F.sigmoid
pass3_block1_mbconv3_detection2_dconv1_eswish_mul_1 = pass3_block1_mbconv3_detection2_dconv1_eswish_mul
pass3_block1_mbconv3_detection2_se_se_squeeze_lambda_Mean = torch.nn.Lambda(lambda x: x * 0.5)
pass3_block1_mbconv3_detection2_se_se_squeeze_lambda_Mean = torch.nn.Lambda(lambda x: x * 0.5)
pass3_block1_mbconv3_detection2_se_se_squeeze_conv_convolution = self
pass3_block1_mbconv3_detection2_se_se_squeeze_eswish_mul = self
pass3_block1_mbconv3_detection2_se_se_squeeze_eswish_Sigmoid = F.sigmoid
pass3_block1_mbconv3_detection2_se_se_squeeze_eswish_mul_1 = pass3_block1_mbconv3_detection2_se_se_squeeze_eswish_mul
pass3_block1_mbconv3_detection2_se_se_excite_conv_convolution = self
pass3_block1_mbconv3_detection2_se_se_excite_sigmoid_Sigmoid = F.sigmoid
pass3_block1_mbconv3_detection2_se_se_multiply_mul = pass3_block1_mbconv3_detection2_se_se_multiply_mul
pass3_block1_mbconv3_detection2_conv2_convolution = self
pass3_block1_mbconv3_detection2_conv2_bn_FusedBatchNorm_1 = self
pass3_block1_mbconv3_detection2_dense_concat = torch.cat((pass3_block1_mbconv3_detection2_conv2_convolution, pass3_block1_mbconv3_detection2_se_se_squeeze_conv_convolution))
pass3_detection2_confs_convolution = self
transposed_convolution_1 = self._transposed(channels=16, kernel_size=3, stride=2, padding=1)
transposed_convolution_2 = self._transposed(channels=16, kernel_size=3, stride=2, padding=1)
transposed_convolution_3 = self._transposed(channels=16, kernel_size=3, stride=2, padding=1)

return transposed_convolution_3
```

.2 E-Swish Source Code

```
def eswish(x):
    """
    E-swish activation with Beta value of 1.25.
    beta = 1.25
    return beta * x * sigmoid(x)
```

.3 Track App Source Code

```
def get_model( framework , model_variant ):
    """
    Load the desired EfficientPose model variant using the requested deeplearning framework
    """

    # Keras
    if framework in [ 'keras ' , 'k ' ]:
```

```
from tensorflow.keras.backend import set_learning_phase
from tensorflow.keras.models import load_model
set_learning_phase(0)
model = load_model(join('models', 'keras', 'EfficientPose{0}.h5'))

# TensorFlow
elif framework in ['tensorflow', 'tf']:
    from tensorflow.python.platform.gfile import FastGFile
    from tensorflow.compat.v1 import GraphDef
    from tensorflow.compat.v1.keras.backend import get_session
    from tensorflow import import_graph_def
    f = FastGFile(join('models', 'tensorflow', 'EfficientPose{0}.pb'), 'r')
    graph_def = GraphDef()
    graph_def.ParseFromString(f.read())
    f.close()
    model = get_session()
    model.graph.as_default()
    import_graph_def(graph_def)

# TensorFlow Lite
elif framework in ['tensorflowlite', 'tflite']:
    from tensorflow import lite
    model = lite.Interpreter(model_path=join('models', 'tflite', 'EfficientPose{0}.tflite'))
    model.allocate_tensors()

# PyTorch
elif framework in ['pytorch', 'torch']:
    from imp import load_source
    from torch import load, quantization, backends
    try:
        MainModel = load_source('MainModel', join('models', 'pytorch', 'EfficientPose{0}.pt'))
    except:
        print('\n#####')
        print('Desired model "EfficientPose{0} Lite" not available in models')
        print('#####')
        return False, False
    model = load(join('models', 'pytorch', 'EfficientPose{0}'.format(model_id)), torch.device('cpu'))
    model.eval()
    qconfig = quantization.get_default_qconfig('qnnpack')
    backends.quantized.engine = 'qnnpack'

return model, {'rt': 224, 'i': 256, 'ii': 368, 'iii': 480, 'iv': 600}

def infer(batch, model, lite, framework):
    """
    Perform inference on supplied image batch.
    """

    # Keras
    if framework in ['keras', 'k']:
```

```
        if lite:
            batch_outputs = model.predict(batch)
        else:
            batch_outputs = model.predict(batch)[-1]

# TensorFlow
elif framework in ['tensorflow', 'tf']:
    output_tensor = model.graph.get_tensor_by_name('upscaled_confs/B
    if lite:
        batch_outputs = model.run(output_tensor, {'input_1_0:0': bat
    else:
        batch_outputs = model.run(output_tensor, {'input_res1:0': ba

# TensorFlow Lite
elif framework in ['tensorflowlite', 'tflite']:
    input_details = model.get_input_details()
    output_details = model.get_output_details()
    model.set_tensor(input_details[0]['index'], batch)
    model.invoke()
    batch_outputs = model.get_tensor(output_details[-1]['index'])

# PyTorch
elif framework in ['pytorch', 'torch']:
    from torch import from_numpy, autograd
    batch = np.rollaxis(batch, 3, 1)
    batch = from_numpy(batch)
    batch = autograd.Variable(batch, requires_grad=False).float()
    batch_outputs = model(batch)
    batch_outputs = batch_outputs.detach().numpy()
    batch_outputs = np.rollaxis(batch_outputs, 1, 4)

return batch_outputs

def analyze_camera(model, framework, resolution, lite):
    """
    Live prediction of pose coordinates from camera.
    """

    # Load video
    import cv2
    start_time = time.time()
    cap = cv2.VideoCapture(0)
    _, frame = cap.read()
    frame_height, frame_width = frame.shape[:2]
    coordinates = []
    print('\n#####')
    while(True):

        # Read frame
        _, frame = cap.read()
```

```
# Construct batch
batch = [frame[...,:-1]]

# Preprocess batch
batch = helpers.preprocess(batch, resolution, lite)

# Perform inference
batch_outputs = infer(batch, model, lite, framework)

# Extract coordinates for frame
frame_coordinates = helpers.extract_coordinates(batch_outputs[0],
coordinates += [frame_coordinates]

# Draw and display predictions
helpers.display_camera(cv2, frame, frame_coordinates, frame_height)

if cv2.waitKey(1) & 0xFF == ord('q'):
    break

cap.release()
cv2.destroyAllWindows()

# Print total operation time
print('Camera operated in {0} seconds'.format(time.time() - start_time))
print('#####')

return coordinates

def analyze_image(file_path, model, framework, resolution, lite):
    """
    Predict pose coordinates on supplied image.
    """

    # Load image
    from PIL import Image
    start_time = time.time()
    image = np.array(Image.open(file_path))
    image_height, image_width = image.shape[:2]
    batch = np.expand_dims(image, axis=0)

    # Preprocess batch
    batch = helpers.preprocess(batch, resolution, lite)

    # Perform inference
    batch_outputs = infer(batch, model, lite, framework)

    # Extract coordinates
    coordinates = [helpers.extract_coordinates(batch_outputs[0], ...), image_height]
```

```
# Print processing time
print('\n#####')
print('Image processed in {0} seconds'.format('%0.3f' % (time.time() - start_time)))
print('#####')

return coordinates

def analyze_video(file_path, model, framework, resolution, lite):
    """
    Predict pose coordinates on supplied video.
    """

    # Define batch size and number of batches in each part
    batch_size = 1 if framework in ['tensorflowlite', 'tflite'] else 49
    part_size = 490 if framework in ['tensorflowlite', 'tflite'] else 10

    # Load video
    from skvideo.io import vreader, ffprobe
    start_time = time.time()
    try:
        videogen = vreader(file_path)
        video_metadata = ffprobe(file_path)['video']
        num_video_frames = int(video_metadata['@nb_frames'])
        num_batches = int(np.ceil(num_video_frames / batch_size))
        frame_height, frame_width = next(vreader(file_path)).shape[:2]
    except:
        print('\n#####')
        print('Video "{0}" could not be loaded. Please verify that the file exists.')
        print('#####')
        return False

    # Operate on batches
    coordinates = []
    batch_num = 1
    part_start_time = time.time()
    print('\n#####')
    while True:

        # Fetch batch of frames
        batch = [next(videogen, None) for _ in range(batch_size)]
        if not type(batch[0]) == np.ndarray:
            break
        elif not type(batch[-1]) == np.ndarray:
            batch = [frame if type(frame) == np.ndarray else np.zeros((frame_height, frame_width, 3)) for frame in batch]

        # Preprocess batch
        batch = helpers.preprocess(batch, resolution, lite)

        # Perform inference
        batch_outputs = infer(batch, model, lite, framework)
```

```
# Extract coordinates for batch
batch_coordinates = [helpers.extract_coordinates(batch_outputs[n],
coordinates += batch_coordinates

# Print partial processing time
if batch_num % part_size == 0:
    print('{0} of {1}: Part processed in {2} seconds | Video pro
    part_start_time = time.time()
batch_num += 1

# Print total processing time
print('{0} of {0}: Video processed in {1} seconds'.format(int(np.cei
print('#####

return coordinates[:num_video_frames]

def analyze(video, file_path, model, framework, resolution, lite):
    """
    Analyzes supplied camera/video/image.
    """

    # Camera-based analysis
    if file_path is None:
        coordinates = analyze_camera(model, framework, resolution, lite)

    # Video analysis
    elif video:
        coordinates = analyze_video(file_path, model, framework, resolution)

    # Image analysis
    else:
        coordinates = analyze_image(file_path, model, framework, resolution)

    return coordinates

def annotate_image(file_path, coordinates):
    """
    Annotates supplied image from predicted coordinates.
    """

    # Load raw image
    from PIL import Image, ImageDraw
    image = Image.open(file_path)
    image_width, image_height = image.size
    image_side = image_width if image_width >= image_height else image_h

    # Annotate image
    image_draw = ImageDraw.Draw(image)
    image_coordinates = coordinates[0]
```

```
image = helpers.display_body_parts(image, image_draw, image_coordinates)
image = helpers.display_segments(image, image_draw, image_coordinates)

# Save annotated image
image.save(normpath(file_path.split('.')[0] + '_tracked.png'))

def annotate_video(file_path, coordinates):
    """
    Annotates supplied video from predicted coordinates.
    """

    # Load raw video
    from skvideo.io import vreader, ffprobe, FFmpegWriter
    videogen = vreader(file_path)
    video_metadata = ffprobe(file_path)['video']
    fps = video_metadata['@r_frame_rate']
    frame_height, frame_width = next(vreader(file_path)).shape[:2]
    frame_side = frame_width if frame_width >= frame_height else frame_h

    # Initialize annotated video
    vcodec = 'libvpx-vp9' #'libx264'
    writer = FFmpegWriter(normpath(file_path.split('.')[0] + '_tracked.m

    # Annotate video
    from PIL import Image, ImageDraw
    i = 0
    while True:
        try:
            frame = next(videogen)
            image = Image.fromarray(frame)
            image_draw = ImageDraw.Draw(image)
            image_coordinates = coordinates[i]
            image = helpers.display_body_parts(image, image_draw, image_co
            image = helpers.display_segments(image, image_draw, image_co
            writer.writeFrame(np.array(image))
            i += 1
        except:
            break

    writer.close()

def annotate(video, file_path, coordinates):
    """
    Analyzes supplied video/image from predicted coordinates.
    """

    # Annotate video predictions
    if video:
        coordinates = annotate_video(file_path, coordinates)
```

```
# Annotate image predictions
else:
    coordinates = annotate_image(file_path, coordinates)

def save(video, file_path, coordinates):
    """
    Saves predicted coordinates as CSV.
    """

    # Initialize CSV
    import csv
    csv_path = normpath(file_path.split('.')[0] + '_coordinates.csv') if
    csv_file = open(csv_path, 'w')
    headers = ['frame'] if video else []
    [headers.extend([body_part + '_x', body_part + '_y']) for body_part,
    writer = csv.DictWriter(csv_file, fieldnames=headers)
    writer.writeheader()

    # Write coordinates to CSV
    for i, image_coordinates in enumerate(coordinates):
        row = {'frame': i + 1} if video else {}
        for body_part, body_part_x, body_part_y in image_coordinates:
            row[body_part + '_x'] = body_part_x
            row[body_part + '_y'] = body_part_y
        writer.writerow(row)

    csv_file.flush()
    csv_file.close()

def perform_tracking(video, file_path, model_name, framework_name, visual
    """
    Process of estimating poses from camera/video/image.
    """

    # VERIFY FRAMEWORK AND MODEL VARIANT
    framework = framework_name.lower()
    model_variant = model_name.lower()
    if framework not in ['keras', 'k', 'tensorflow', 'tf', 'tensorflowli
        print('\n#####
        print('Desired framework "{0}" not available. Please select amon
        print(#####
        return False
    elif model_variant not in ['efficientposert', 'rt', 'efficientposei
        print('\n#####
        print('Desired model "{0}" not available. Please select among "R
        print(#####
        return False

    # LOAD MODEL
    else:
```



```
        model_variant = model_variant[13:] if len(model_variant) > 7 else
        lite = True if model_variant.endswith('_lite') else False
        model, resolution = get_model(framework, model_variant)
        if not model:
            return True

# PERFORM INFERENCE
coordinates = analyze(video, file_path, model, framework, resolution)

# VISUALIZE PREDICTIONS
if visualize and file_path is not None and coordinates:
    annotate(video, file_path, coordinates)

# STORE PREDICTIONS AS CSV
if store and coordinates:
    save(video, file_path, coordinates)

return True

def main(file_path, model_name, framework_name, visualize, store):
    """
    Main program for performing tracking from camera or video or pose es

    # LIVE ANALYSIS FROM CAMERA
    if file_path is None:
        print('\n#####')
        print('Click "Q" to end camera-based tracking.'.format(file_path))
        print('#####')
        perform_tracking(video=True, file_path=None, model_name=model_name)

    # VIDEO ANALYSIS
    elif 'Video' in [track.track_type for track in MediaInfo.parse(file_path)]:
        perform_tracking(video=True, file_path=normpath(file_path), model_name=model_name)

    # IMAGE ANALYSIS
    elif 'Image' in [track.track_type for track in MediaInfo.parse(file_path)]:
        perform_tracking(video=False, file_path=normpath(file_path), model_name=model_name)

    else:
        print('\n#####')
        print('Ensure supplied file "{0}" is a video or image'.format(file_path))
        print('#####')

if __name__ == '__main__':

    # Fetch arguments
    args = sys.argv[1:]

    # Define options
    short_options = 'p:m:f:vs'
```

```
long_options = [ 'path=', 'model=', 'framework=', 'visualize ', 'store'
try:
    arguments, values = getopt(args, short_options, long_options)
except error as err:
    print('\n#####')
    print(str(err))
    print('#####')
    sys.exit(2)

# Define default choices
file_path = None
model_name = 'I_Lite'
framework_name = 'TFLite'
visualize = False
store = False

# Set custom choices
for current_argument, current_value in arguments:
    if current_argument in ('-p', '--path'):
        file_path = current_value if len(current_value) > 0 else None
    elif current_argument in ('-m', '--model'):
        model_name = current_value
    elif current_argument in ('-f', '--framework'):
        framework_name = current_value
    elif current_argument in ('-v', '--visualize'):
        visualize = True
    elif current_argument in ('-s', '--store'):
        store = True
print('\n#####')
print('The program will attempt to analyze {0} using the "{1}" framework'.format(file_path, model_name))
print('#####')

main(file_path=file_path, model_name=model_name, framework_name=framework_name, visualize=visualize, store=store)
```