

YOLO5Face: Why Reinventing a Face Detector

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Abstract

Tremendous progress has been made on face detection in recent years using convolutional neural networks. While many face detectors use designs designated for detecting faces, we treat face detection as a generic object detection task. We implement a face detector based on the YOLOv5 object detector and call it YOLO5Face. We make a few key modifications to the YOLOv5 and optimize it for face detection. These modifications include adding a five-point landmark regression head, using a stem block at the input of the backbone, using smaller-size kernels in the SPP, and adding a P6 output in the PAN block. We design detectors of different model sizes, from an extra-large model to achieve the best performance to a super small model for real-time detection on an embedded or mobile device. Experiment results on the WiderFace dataset show that on VGA images, our face detectors can achieve state-of-the-art performance in almost all the Easy, Medium, and Hard subsets, exceeding the more complex designated face detectors. The code is available at <https://github.com/deepcam-cn/yolov5-face>.

1. Introduction

Face detection is an important computer vision task. As the first step of many tasks, including face recognition, verification, tracking, alignment, expression analysis, face detection attracts many research and developments in academia and the industry. Tremendous progress has been made since deep learning, particularly convolutional neural network (CNN), has been used in this task. And the performance of face detection has improved significantly over the years. For a survey of face detection, please refer to the benchmark results [40, 39].

There are many methods in this field from different perspectives. Research directions include the design of the CNN network, loss functions, data augmentations, and training strategies. For example, in the YOLOv4 paper,

the authors explore all these research directions and propose the YOLOv4 object detector based on optimizations of network architecture, selection of bags of freebies, and selection of bags of specials [2].

In our approach, we treat face detection as a generic object detection task. We have the same intuition as the TinaFace [57]. Intuitively, a face is an object. As discussed in the TinaFace [57], from the perspective of data, the properties that face has, like pose, scale, occlusion, illumination, blur, etc., also exist in other objects. The unique properties in faces like expression and makeup can also correspond to distortion and color in objects. Landmarks are special to face, but they are not unique either. They are just key points of an object. For example, in license plate detection, landmarks are also used. And adding landmark regression in the object prediction head is straightforward. Then from the perspective of challenges encountered by face detection like multi-scale, small faces, and dense scenes, they all exist in generic object detection. Thus, face detection is just a sub-task of generic object detection.

In this paper, we follow this intuition and design a face detector based on the YOLOv5 object detector [42]. We modify the design for face detection considering large faces, small faces, landmark supervision for different complexities and applications. Our goal is to provide a portfolio of models for various applications, from very complex ones to get the best performance to very simple ones to get the best trade-off of performance and speed on embedded or mobile devices.

Our main contributions are summarized as follows,

- We redesign the YoloV5 object detector [42] as a face detector, and call it YOLO5Face. We implement key modifications to the network to improve the performance in terms of mean average precision (mAP) and speed. The details of these modifications will be presented in Section III.
- We design a series of models of different model sizes, from large models, to medium models, to super small

models, for needs in different applications. In addition to the backbone used in YOLOv5 [42], we implement a backbone based on ShuffleNetV2 [26], which gives the state-of-the-art (SOTA) performance and fast speed for mobile devices.

- We evaluate our models on the WiderFace [40] dataset. On VGA resolution images, almost all our models achieve the start-of-the-art (SOTA) performance and fast speed. We also evaluate it on the FDDB dataset [36]. A face recognition evaluation on the Webface dataset [58] demonstrates better landmark accuracy than the RetinaFace [8]. This answers the question in the title of this paper. We delicately design a face detector based on YOLOv5 [42] that is as good as or better than other face detectors specifically invented for face detection.

Please note that our contribution is not exploring a novel idea but rather a delicate redesign of an existing idea for a specific application. Since we open-source the code, many applications and mobile apps have been developed based on our design and achieve impressive performance, which demonstrates the value of our work to the face detection community.

2. Related Work

2.1. Object Detection

General object detection aims at locating and classifying the pre-defined objects in a given image. Before deep CNN is used, traditional face detection uses hand-crafted features, like HAAR, HOG, LBP, SIFT, DPM, ACF, etc. The seminal work by Viola and Jones [53] introduces integral images to compute HAAR-like features. For a survey of face detection using hand-crafted features, please refer to [38, 54].

Since deep CNN shows its power in many machine learning tasks, face detection is dominated by deep CNN methods. There are two-stage and one-stage object detectors. Typical two-stage methods are the RCNN family, including RCNN [12], fast-RCNN [11], faster-RCNN [30], mask-RCNN [14], Cascade-RCNN [3].

The two-stage object detector has excellent performance but suffers from long latency and slow speed. Therefore, one-stage object detectors are studied to overcome this problem. Typical one-stage networks include SSD [23], YOLO [27, 29, 28, 2, 42].

Other object detection networks include FPN [21], MMDetection [5], EfficientDet [33], transformer(DETR) [4], Centernet [9, 56], and so on.

2.2. Face Detection

The researches for face detection follows the general object detection. After the most popular and challenging face detection benchmark WiderFace dataset [40] is released, face detection develops rapidly, focusing on the extreme and real variation problem including scale, pose, occlusion, expression, makeup, illumination, blur, etc.

A lot of methods are proposed to deal with these problems, particularly the scale, context, anchor in order to detect small faces. These methods include MTCNN [44], FaceBox [48], S3FD [49], DSFD [19], RetinaFace [8], RefineFace [45], DFS [35], VIM-FD [51], SRN [6], ISRN [47], SFDet [46], PyramidBox [34], PyramidBox++ [20], and the most recent ASFD [43], MaskFace [41], TinaFace [57], MogFace [25], and SCRFD [13]. For a list of popular face detectors, the readers are referred to the WiderFace website [39].

It is worth noting that some of these face detectors explore unique characteristics in a human face; the others are just general object detectors adopted and modified for face detection. Using RetinaFace [8] as an example, it uses face landmark and mesh (2D and 3D) regression to help the supervision of face detection, while TinaFace [57] is simply a general object detector.

2.3. YOLO

YOLO first appeared in 2015 [27] as a different approach than popular two-stage approaches. It treats object detection as a regression problem rather than a classification problem. It performs all the essential stages to detect an object using a single neural network. As a result, it achieves not only good detection performance but also achieves real-time speed. Furthermore, it has excellent generalization capability, can be easily trained to detect different objects.

Over the next five years, the YOLO algorithm has been upgraded to five versions with many innovative ideas from the object detection community. The first three versions - YOLOv1 [27], YOLOv2 [29], YOLOv3 [28] is developed by the author of the original YOLO algorithm. Out of these three versions, the YOLOv3 [28] is a milestone with big improvements in performance and speed by introducing multi-scale features (FPN) [21], a better backbone network (Darknet53), and replacing the Softmax classification loss with the binary cross-entropy loss.

In early 2020, after the original YOLO authors withdrew from the research field, YOLOv4 [2] was released by a different research team. The team explores a lot of options in almost all aspects of the YOLOv3 [28] algorithm, including the backbone and what they call bags of freebies and bags of specials. It achieves 43.5% AP (65.7% AP50) for the MS COCO dataset at a real-time speed of 65 FPS on the Tesla V100.

One month later, the YOLOv5 [42] was released by another different research team. In the algorithm perspective, the YOLOv5 [42] does not have many innovations. And the team does not publish a paper. These bring quite some controversies about if it should be called YOLOv5. However, due to its significantly reduced model size, faster speed, and similar performance as YOLOv4 [2], and full implementation in Python (Pytorch), it is welcome by the object detection community.

3. YOLO5Face Face Detector

In this section, we present the key modifications we make in YOLOv5 and make it a face detector - YOLO5Face.

3.1. Summary Key Modifications

A summary of these modifications is listed below. More details will be given in the following subsections.

1. We add a landmark regression head.
2. We replace the Focus layer with a stem block structure.
3. We change the SPP block [15] to use smaller kernels.
4. We add a P6 output block with a stride of 64.
5. We design two super light-weight models based on ShuffleNetV2 [26] backbone.
6. We optimize data augmentation methods specifically good for face detection.

3.2. Network Architecture

We use the YOLOv5 object detector [42] as our baseline and optimize it for face detection. We introduce some modifications designated for the detection of small faces as well as large faces.

The network architecture of our YOLO5Face face detector is depicted in Fig. 1. The diagram style is borrowed from [22]. All our modified blocks are highlighted in red. It consists of the backbone with FPN, FAN neck, and output head. In YOLOv5, a newly designed backbone block called CSPNet [42] is used. Near the end of the backbone, an SPP block is used. In the neck, a PAN [22] is used to aggregate the features. In the output head, regression and classification are both used. In the YOLOv5 [42] design, there is a focus layer at the input. We replace this focus layer with a stem unit.

In Fig. 1 (c), an output label for the head include bounding box (box), confidence (conf), classification (class) and five-point landmarks. The landmarks are our addition to the YOLOv5 to make it a face detector with landmark output. If without the landmark, the last dimension 16 should be 6. Please note that the output dimensions 80*80*16 in P3, 40*40*16 in P4, 20*20*16 in P5, 10*10*16 in optional P6 are for every anchor. The real dimension should be multiplied by the number of anchors.

In the SPP block, the three kernel sizes 13x13, 9x9, 5x5 in YOLOv5 are revised to 7x7, 5x5, 3x3 in our face detector. This has been shown as one of the innovations that improve face detection performance.

Note that we only consider VGA resolution input images. To be more precise, the longer edge of the input image is scaled to 640, and the shorter edge is scaled accordingly. The shorter edge is also adjusted to be a multiple of the largest stride of the SPP block. For example, when P6 is not used, the shorter edge needs to be multiple of 32; when P6 is used, the shorter edge needs to multiple of 64.

3.3. Landmark Regression

Landmarks are important characteristics of the human face. They can be used to do face alignment, face recognition, face express analysis, age analysis, etc. Traditional landmarks consist of 68 points. They are simplified to 5 points in MTCNN [44] Since then, the five-point landmarks have been used widely in face recognition. The quality of landmarks affects the quality of face alignment and face recognition.

The general object detector does not include landmarks. It is straightforward to add it as a regression head. Therefore, we add it to our YOLO5Face. The landmark outputs will be used in align face images before they are sent to the face recognition network.

General loss functions for landmark regression are L2, L1, or smooth-L1. The MTCNN [44] uses the L2 loss function. However, it is found these loss functions are not sensitive to small errors. To overcome this problem, the Wing-loss is proposed [10],

$$wing(x) = \begin{cases} w \cdot \ln(1 + |x|/e), & \text{if } x < w \\ |x| - C, & \text{otherwise} \end{cases} \quad (1)$$

The non-negative w sets the range of the nonlinear part to $(-w, w)$, e limits the curvature of the nonlinear region, and $C = w - w\ln(1 + w/e)$ is a constant that smoothly links the piecewise-defined linear and nonlinear parts. As pointed out in [10], in the Wing loss function, the response at a small error area near zero is boosted compared to the L2, L1, or smooth-L1 functions.

The loss functions for landmark point vector $s = \{s_i\}$, and its ground truth $s' = \{s'_i\}$, where $i = 1, 2, \dots, 10$, is defined as,

$$loss_L(s) = \sum_i wing(s_i - s'_i) \quad (2)$$

Let the general object detection loss function of YOLOv5 be $loss_{obj}(bounding_box, class, probability)$, then the new total loss function is,

$$loss(s) = loss_{obj} + \lambda_L \cdot loss_L \quad (3)$$

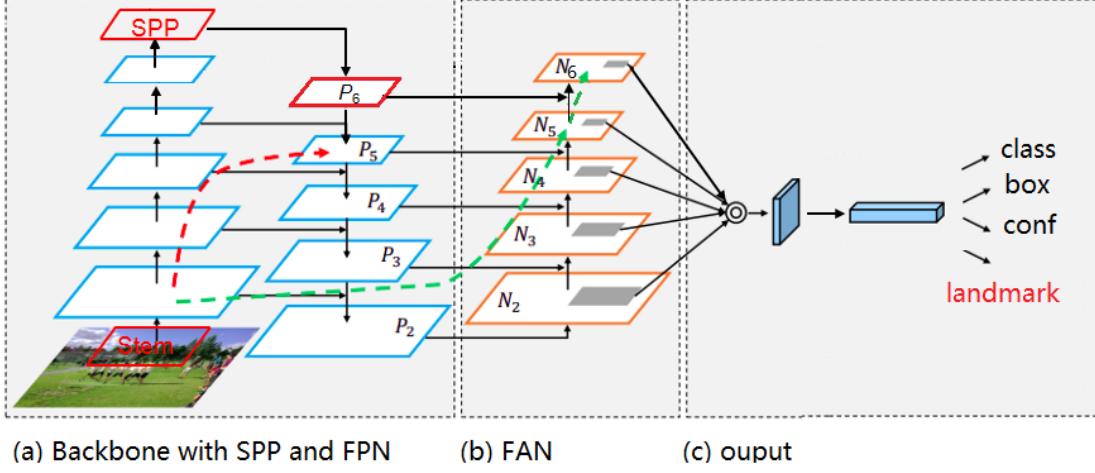


Figure 1. The proposed YOLO5Face network architecture. The style of the diagram is borrowed from [22].

where the λ_L is a weighting factor for the landmark regression loss function. Details of $loss_{obj}$ can be found in the appendix.

3.4. Stem Block Structure

In a standard network like ResNet [16] there is a stem unit - a component whose goal is to reduce the input resolution quickly. The ResNet50 stem is comprised of a stride-2 conv 7×7 followed by a max-pooling layer [16]. The ResNet50-D [17] stem design is more elaborate - the conv 7×7 is replaced by three conv 3×3 layers. The new ResNet50-D stem design improves accuracy but at the cost of lowering the training throughput. In the TResNet [31], the stem unit is called a DepthToSpace transformation layer, which aims to replace the traditional convolution-based downsampling unit with a fast and seamless layer, with as little information loss as possible. It has been reported in [17], and [31] that a better-designed stem unit can improve the classification accuracy.

We design a stem block similar to [37], as shown in Fig. 1 (d). In this stem block, we implement a stride = 2 in the first spatial down-sampling on the input image and increase the number of channels. With this stem block, the computation complexity only increases marginally while a better performance may be achieved. Experiment data will be presented in the ablation study.

3.5. SPP with Smaller Kernels

Before forwarding to the feature aggregation block in the neck, the output feature maps of the YOLO5 backbone are sent to an additional SPP block [15] to increase the receptive field and separate out the most important features. Instead of many CNN models containing fully connected layers which only accept input images of specific dimensions,

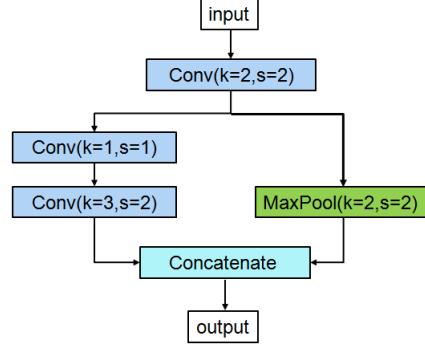


Figure 2. Stem block structure to replace the focus layer.

Model	Backbone	(D,W)	P6?
YOLOv5n	ShuffleNetv2	-	No
YOLOv5n-0.5	ShuffleNetv2-0.5	-	No
YOLOv5s	YOLO5-CSPNet	(0.33,0.50)	No
YOLOv5s6	YOLO5-CSPNet	(0.33,0.50)	Yes
YOLOv5m	YOLO5-CSPNet	(0.50,0.75)	No
YOLOv5m6	YOLO5-CSPNet	(0.50,0.75)	Yes
YOLOv5l	YOLO5-CSPNet	(1.0,1.0)	No
YOLOv5l6	YOLO5-CSPNet	(1.0,1.0)	Yes
YOLOv5x	YOLO5-CSPNet	(1.33,1.25)	No
YOLOv5x6	YOLO5-CSPNet	(1.33,1.25)	Yes

Table 1. Detail of implemented YOLO5Face models, where (D,W) are the depth and width multiples of the YOLOv5-CSPNet [42]. The ShuffleNetv2 [26] is used as the backbone in the two super-small models. The number of parameters and Flops are listed in Table 4.

SPP is proposed to aim at generating a fixed-size output irrespective of the input size. In addition, SPP also helps to extract important features by pooling multi-scale versions of itself.

In YOLO5, three kernel sizes 13x13, 9x9, 5x5 are used [42]. We revise them to use smaller size kernels 7x7, 5x5, and 3x3. These smaller kernels help to detect small faces more easily and increase the overall face detection performance. Qualitative evaluation will be shown in the ablation study.

3.6. P6 Output Block

A key component of YOLOv4 [2], and YOLOv5 [42] is the path aggregation network (PAN) [22], which helps the preserving and passing of fine-grained features in deep layers.

In YOLOv5, there are three output blocks in the PAN output feature maps, called P3, P4, P5, corresponding to 80x80x16, 40x40x16, 20x20x16, with strides 8, 16, 32, respectively. The face bounding box, landmarks, and confidence are regressed from these blocks. In our YOLO5Face, we add an extra P6 output block, whose feature map is 10x10x16 with stride 64. This modification particularly helps the detection of large faces. While almost all face detectors focus on improving the detection of small faces, detection of large faces can be easily overlooked. We fill this hole by adding the P6 output block. Qualitative evaluation will be shown in the ablation study.

3.7. ShuffleNetV2 as Backbone

For applications in embedding or mobile devices, a lightweight backbone is used to reduce the computation complexity and increase speed. Two popular choices are MobileNet [32] and ShuffleNet [50]. The ShuffleNetV2 [50] borrows the idea of a shortcut path similar to that in DenseNet [18], and uses channel shuffling to mix features. This makes the ShuffleNetV2 a super-fast network.

We use the ShuffleNetV2 as the backbone in YOLOv5 and implement super small face detectors YOLOv5n-Face, and YOLOv5n0.5-Face.

3.8. Data Augmentation for Face Detection

We find that some data augmentation methods on general object detection are not appropriate for face detection, including up-down flipping and Mosaic. Removing the up-down flipping improves the performance. When small images are used, the Mosaic augmentation [2] degrades the performance. However, when the small faces are ignored, it works well. Random cropping helps the performance. More details can be found in the ablation study.

4. Experiments

4.1. Dataset

The WiderFace dataset [40] is the largest face detection dataset, which contains 32,203 images and 393,703 faces.

For its large variety of scale, pose, occlusion, expression, illumination, and event, it is close to reality and is very challenging.

The whole dataset is divided into train/validation/test sets by ratio 50%/10%/40% within each event class. Furthermore, each subset is defined into three levels of difficulty: Easy, Medium, and Hard. As it names indicates, the Hard subset is most challenging. So the performance on the Hard subset best reflects the effectiveness of a face detector.

Unless specified otherwise, the WiderFace dataset [40] is used in this work. In the face recognition with YOLO5Face landmark and alignment, the Webface dataset [58] is used. The FDDB dataset [36] is used in testing to demonstrate our model’s performance on cross-domain datasets.

4.2. Implementation Details

We use the YOLOv5 codebase [42] as our starting point and implement all the modifications we describe earlier in PyTorch.

The SGD optimizer is used. The initial learning rate is 1E-2, the final learning rate is 1E-5, and the weight decay is 5E-3. A momentum of 0.8 is used in the first three warming-up epochs. After that, the momentum is changed to 0.937. The training runs 250 epochs with a batch size of 64. The $\lambda_L = 0.5$ is optimized by exhaust search.

Implemented Models. We implement a series of face detector models, as listed in Table 1. We implement eight relatively large models, including extra large-size models (YOLOv5x, YOLOv5x6), large-size models (YOLOv5l, YOLOv5l6) medium-size models (YOLOv5m, YOLOv5m6), and small-size models (YOLOv5s, YOLOv5s6). In the name of the model, the last postfix 6 means it has the P6 output block in the SPP. These models all use the YOLOv4 CSPNet as the backbone with different depth and width multiples, denoted as D and W in Table 1.

Furthermore, we implement two super small-size models, YOLOv5n and YOLOv5n0.5, which use the ShuffleNetV2 and ShuffleNetV2-0.5 [26] as the backbone. Except for the backbone, all other main blocks, including the stem block, SPP, PAN, are the same as in the larger models.

The number of parameters and number of flops of all these models is listed in Table 4 for comparison with existing methods.

4.3. Ablation Study

In this subsection, we present the effects of the modifications we have in our YOLO5Face. In this study, we use the YOLO5s model. We use the WiderFace [40] validation dataset and use the mAP as the performance metric. The results are presented in Table 2. Please note we do the experiments incrementally, where we add a modification at a time.

Modification	Easy	Medium	Hard
Baseline (Focus block)	94.70	92.90	83.27
+ Stem block	94.46	92.72	83.57
+ Landmark	94.47	92.79	83.21
+ SPP(3,5,7)	94.66	92.83	83.33
+ Ignore small faces	94.71	93.01	83.33
+ P6 block	95.29	93.61	83.27

Table 2. Ablation study results on the WiderFace validation dataset.

FaceDetect	traning dataset	FNMR
RetinaFace[8]	WiderFace [40]	0.1065
YOLOv5s	WiderFace	0.1060
YOLOv5s	+Multi-task facial[52]	0.1058
YOLOv5m	WiderFace	0.1056
YOLOv5m	+Multi-task facial	0.1051

Table 3. Evaluation of YOLO5Face landmark on Webface test dataset [58]. Retina refers to the RetinaFace [45]. Two YOLO5Face models, the small model YOLOv5s, and the medium model YOLOv5m are used.

Stem Block We use the standard YOLOv5 [42] as a baseline which has a focus layer. By replacing the focus layer with our stem block, the mAP on the hard subset increased by 0.30%, which is non-trivial. The mAPs on the easy and medium subsets degrades slightly.

Landmark. Landmarks are used in many applications, including face recognition, where the landmarks are used to align the detected face image. Using the stem block as a baseline, adding the landmark achieves about the same performance on the easy and medium subsets while causes a little performance loss on the hard dataset. We will show in the next subsection the benefits of our landmarks to face recognition.

SPP with Smaller Size Kernels. The stem block and landmark are used in this test. The SPP kernel sizes (13x13, 9x9, 5x5) are changed to (7x7, 5x5, 3x3). mAPs are improved in all easy, medium, and hard subsets. The mAPs are improved by 0.1-0.2%.

Data Augmentation. A few data augmentation methods are studied. We find that ignoring small faces combined with random crop and Mosaic [2] helps the mAPs. It improves the mAPs on the easy and medium subset by 0.1-0.2%.

P6 Output Block. The P6 block brings significant mAP improvements, about 0.5-0.6%, on the easy and medium subsets. Perhaps motivated by our findings, the P6 block is added to YOLOv5 [42] after us.

Please note that since we do not use exactly the same parameters in this ablation study as in the final benchmark tests, the results in Table 2 may be slightly different from that in Table 4.



Figure 3. Some examples of detected face and landmarks, where the first row is from RetinaFace [8], and second row is from our YOLOv5m.

4.4. YOLO5Face for Face Recognition

Landmark is critical for face recognition accuracy. In RetinaFace [8], the accuracy of the landmark is evaluated with the MSE between estimated landmark coordinates and their ground truth and with the face recognition accuracy. The results show that the RetinaFace has better landmarks than the older MTCNN [44].

In this work, we also use face recognition to evaluate the accuracy of landmarks of the YOLO5Face. We use the Webface test dataset, which is the largest face dataset with noisy 4M identities/260M faces, and cleaned 2M identities/42M faces [58]. This dataset is used in the ICCV2021 Masked Face Recognition (MFR) challenge. In this challenge, both masked face images and standard face images are included, and a metric False Non-Match Rate (FNMR) at False Match Rate (FMR) = 1E-5 is used. The FNMR*0.25 for MFR plus FNMR*0.75 for standard face recognition is combined as the final metric.

By default, the RetinaFace [17] is used as the face detector on the dataset. We compare our YOLO5Face with the RetinaFace on this dataset. We use ArcFace [7] framework with Resnet124 [16] as backbone. Extracted features of two models trained on the Glint360k dataset [1] are concatenated as the baseline model. We replace the RetinaFace with our YOLO5Face. We test two models, a small model YOLOv5s, and a medium model YOLOv5m.

The results are listed in Table 3. From the results, we see that both our small and medium models outperform the RetinaFace [8]. In addition, we notice that there are very few large face images in the WiderFace dataset, so we add some large face images from the Multi-task-facial dataset [52] into the YOLO5Face training dataset. We find that this technique improves face recognition performance.

shown in Figure 3 are some detected Webface [58] faces and landmarks using the RetinaFace [8] and our YOLOv5m. On the faces of a large pose, we can visually observe that our landmarks are more accurate, which has been proved in our face recognition results shown in Table 3.

Detector	Backbone	Easy	Medium	Hard	Params(M)	Flops(G)
DSFD [19]	ResNet152 [16]	94.29	91.47	71.39	120.06	259.55
RetinaFace [8]	ResNet50 [16]	94.92	91.90	64.17	29.50	37.59
HAMBox [24]	ResNet50 [16]	95.27	93.76	76.75	30.24	43.28
TinaFace [57]	ResNet50 [16]	95.61	94.25	81.43	37.98	172.95
SCRFD-34GF [13]	Bottleneck ResNet	96.06	94.92	85.29	9.80	34.13
SCRFD-10GF [13]	Basic ResNet [16]	95.16	93.87	83.05	3.86	9.98
Our YOLOv5s	YOLOv5-CSPNet [42]	94.33	92.61	83.15	7.075	5.751
Our YOLOv5s6	YOLOv5-CSPNet	95.48	93.66	82.8	12.386	6.280
Our YOLOv5m	YOLOv5-CSPNet	95.30	93.76	85.28	21.063	18.146
Our YOLOv5m6	YOLOv5-CSPNet	95.66	94.1	85.2	35.485	19.773
Our YOLOv5l	YOLOv5-CSPNet	95.9	94.4	84.5	46.627	41.607
Our YOLOv5l6	YOLOv5-CSPNet	96.38	94.90	85.88	76.674	45.279
Our YOLOv5x6	YOLOv5-CSPNet	96.67	95.08	86.55	141.158	88.665
SCRFD-2.5GF [13]	Basic Resnet	93.78	92.16	77.87	0.67	2.53
SCRFD-0.5GF [13]	Depth-wise Conv	90.57	88.12	68.51	0.57	0.508
RetinaFace [8]	MobileNet0.25[32]	87.78	81.16	47.32	0.44	0.802
FaceBoxes [48]	-	76.17	57.17	24.18	1.01	0.275
Our YOLOv5n	ShuffleNetv2 [26]	93.61	91.54	80.53	1.726	2.111
Our YOLOv5n0.5	ShuffleNetv2-0.5 [26]	90.76	88.12	73.82	0.447	0.571

Table 4. Comparison of our YOLO5Face and existing face detectors on the WiderFace validation dataset [40].

4.5. YOLO5Face on WiderFace Dataset

We compare our YOLO5Face with many existing face detectors on the WiderFace dataset. The results are listed in Table 4, where the previous SOTA results and our best results are both highlighted.

We first look at the performance of relatively large models whose number of parameters is larger than 3M and the number of flops is larger than 5G. All existing methods achieve mAP in 94.27-96.06% on the Easy subset, 91.9-94.92% on the Medium subset, and 71.39-85.29% on the Hard subset. The most recently released SCRFD [13] achieves the best performance in all subsets. Our YOLO5Face (YOLOv5x6) achieves 96.67%, 95.08%, 86.55% on the three subsets, respectively. We achieve the SOTA performance on all the Easy, Medium, and Hard subsets.

Next, we look at the performance of super small models whose number of parameters is less than 2M and the number of flops is less than 3G. All existing methods achieve mAP in 76.17-93.78% on the Easy subset, 57.17-92.16% on the Medium subset, and 24.18-77.87% on the Hard subset. Again, the SCRFD [13] achieves the best performance in all subsets. Our YOLO5Face (YOLOv5n) achieves 93.61%, 91.54%, 80.53% on the three subsets, respectively. Our face detector has a little bit worse performance than the SCRFD [13] on the Easy and Medium subsets. However, on the Hard subset, our face detector is leading by 2.66%. Furthermore, our smallest model, YOLOv5n0.5, has good performance, even its model size is much smaller.

The precision-recall (PR) curves of our YOLO5Face

Method	MAP
ASFD [43]	0.9911
RefineFace [45]	0.9911
PyramidBox [34]	0.9869
FaceBoxes [48]	0.9598
Our YOLOv5s	0.9843
Our YOLOv5m	0.9849
Our YOLOv5l	0.9867
Our YOLOv5l6	0.9880

Table 5. Evaluation of YOLO5Face on the FDDB dataset [36].

face detector, along with the competitors, are shown in Figure 4. The leading competitors include DFS [35], ISRN [47], VIM-FD [51], DSFD [19], PyramidBox++ [20], SRN [6], PyramidBox [34] and more. For a full list of the competitors and their results on the WiderFace [40] validation and test datasets, please refer to [39]. In the results on the validation dataset, our YOLOv5x6-Face detector achieves 96.9%, 96.0%, 91.6% mAP on the Easy, Medium, and Hard subset, respectively, exceeding the previous SOTA by 0.0%, 0.1%, 0.4%. In the results on the test dataset, our YOLOv5x6-Face detector achieves 95.8%, 94.9%, 90.5% mAP on the Easy, Medium, and Hard subset, respectively with 1.1%, 1.0%, 0.7% gap to the previous SOTA. Please note that, in these evaluations, we only use multiple scales and left-right flipping without using other test-time augmentation (TTA) methods. Our focus is more on the VGA input images, where we achieve the SOTA in almost all conditions.

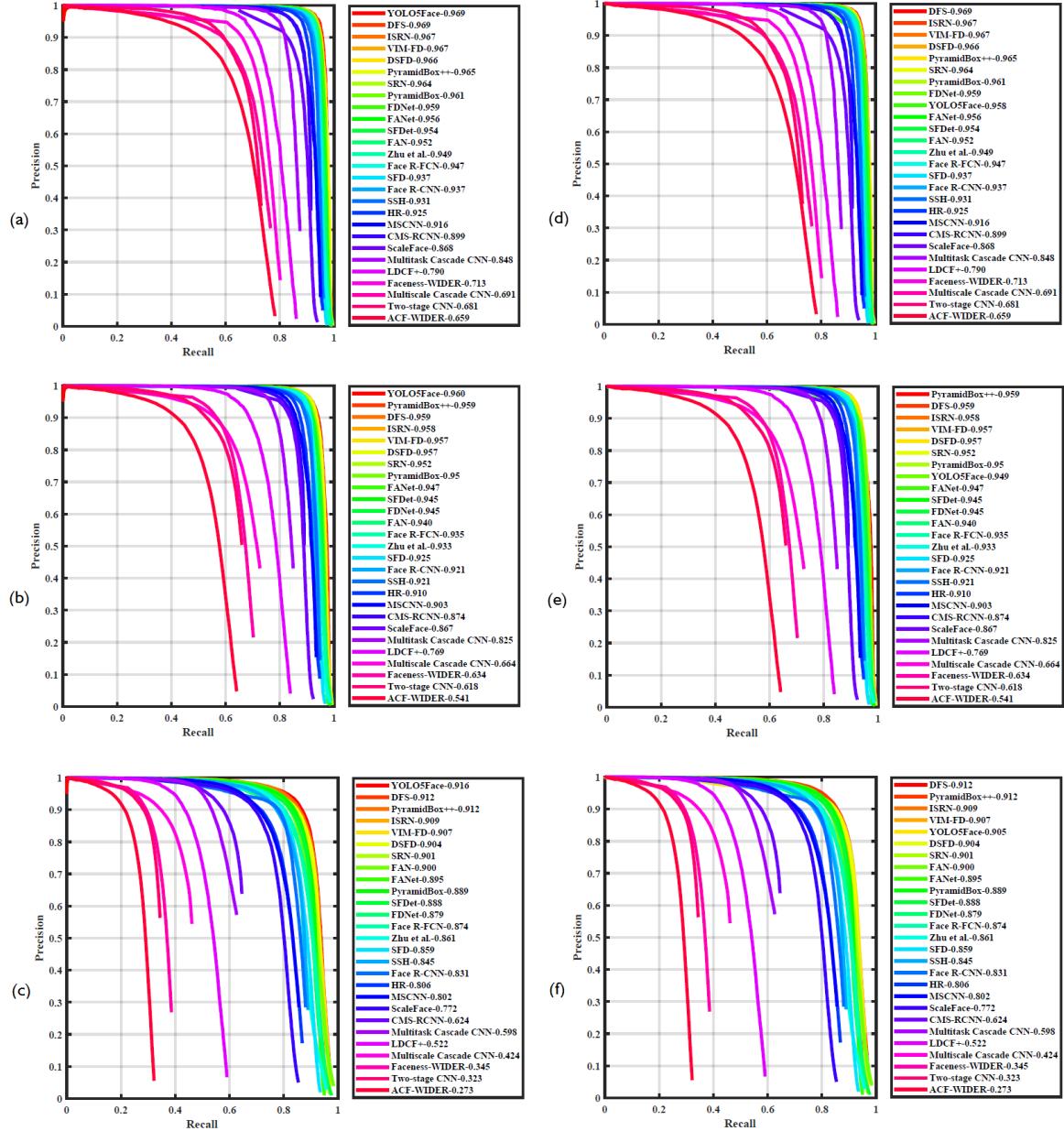


Figure 4. The precision-recall (PR) curves of face detectors, (a) validation-Easy, (b) validation-Medium, (c) validation-Hard, (d) test-Easy, (e) test-Medium, (f) test-Hard.

4.6. YOLO5Face on FDDB Dataset

FDDB dataset [36] is a small dataset with 5171 faces annotated in 2845 images. To demonstrate our YOLO5Face’s performance on the cross-domain dataset, we test it on the FDDB dataset without retraining on it. The performances of true positive rate (TPR) when the number of false-positive is 1000 are listed in Table 4. Please note that it is pointed out in RefineFace [45] that the annotation of FDDB misses many faces. In order to achieve their perfor-

mance of 0.9911, the RefineFace modifies the FDDB annotation. In our evaluation, we use the original FDDB annotation without modifications. RetinaFace [8] is not evaluated on the FDDB dataset.

5. Conclusion

In this paper, we present our YOLO5Face based on YOLOv5 object detector [42]. We implement ten models. Both the super large model YOLOv5x6 and the su-

per small model YOLOv5n achieve close to or exceeding SOTA performance on the VGA images on the WiderFace [40] validation datasets. This proves the effectiveness of our YOLO5Face in not only achieving outstanding prediction accuracy but also running fast. This answers the question in the title. By delicately redesigning YOLOv5, we can obtain a face detector as good as or better than other detectors specifically designed for face detection.

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A. YOLOv5 Loss Function

The details of the YOLOv5 [42] loss function $loss_{obj}(bounding_box, class, probability)$ are given in this appendix.

YOLOv3 loss function. Let's start with the YOLOv3 [28] loss function. Define the center coordinate of a bounding box as (x_i, y_i) , width and height as w_i, h_i , class as C_i . A hat denotes an object's ground truth. Define $I_{i,j}^{obj} = 1$ if there is an object (obj) at grid (i,j), otherwise it is 0. And define $I_{i,j}^{noobj} = 1$ if there is no object (noobj) at grid (i,j), otherwise it is 0. The the YOLOv3 loss function is defied in Equation (4),

$$\begin{aligned}
loss_{loc} &= \lambda_{coord} \sum_{i=0}^{K^2} \sum_{j=0}^M I_{i,j}^{obj} (2 - w_i \times h_i) \\
&\quad [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 + (w_i - \hat{w}_i)^2 + (h_i - \hat{h}_i)^2], \\
loss_{cls} &= -\lambda_{class} \sum_{i=0}^{K^2} \sum_{j=0}^M I_{i,j}^{obj} \sum_{c \in classes} [p_i(c) \log(\hat{p}_i(c)) \\
&\quad + (1 - \hat{p}_i(c)) \log(1 - p_i(c))], \\
loss_{conf} &= -\lambda_{noobj} \sum_{i=0}^{K^2} \sum_{j=0}^M I_{i,j}^{noobj} [\hat{C}_i \times \log(C_i) \\
&\quad + (1 - \hat{C}_i) \times (1 - \log(C_i))] \\
&\quad - \sum_{j=0}^M I_{i,j}^{obj} [\hat{C}_i \times \log(C_i) + (1 - \hat{C}_i) \times (1 - \log(C_i))], \\
loss &= loss_{loc} + loss_{conf} + loss_{cls}
\end{aligned} \tag{4}$$

where $loss_{loc}$ is the bounding box location regression loss, $loss_{conf}$ is the confidence loss, and $loss_{cls}$ is the classification loss, and all λ 's are weighting factors. In this loss function, there are KxK grids and M anchors in every grid, and a bounding box predicted for every anchor. So in total, there are KxKxM bounding boxes. If there is no object in an box, then only the confidence loss is calculated. Please note that,

- The regression loss is multiplied by a $(2-w^*h)$ scale factor. This is to penalize the loss for small objects.
- The confidence loss function uses cross entropy and is divided into two parts: there are objects and no objects, and the loss of noobj also increases the weight coefficient, which is to reduce the calculation part without objects Contribution weight.
- The classification loss loss function uses cross entropy. When the j_{th} anchor box of the i_{th} grid is responsible for a real target, then the bounding box generated by

this anchor box is used to calculate the classification loss function.

YOLOv4 loss function. Different from YOLOv3 [28], YOLOv4 [2] uses different location loss. It does not use the MSE loss; instead, it uses a complete IoU (CIoU) loss [55]. For bounding box, this CIoU loss considers more information then the IoU, including overlapping of the edges, distance of centers, and ratio of the width to height.

$$\begin{aligned}
v &= 4/\pi^2 [\arctan(w^{gt}/h^{gt}) - \arctan(w/h)]^2 \\
\alpha &= v/[1 - IoU + v] \\
loss_{loc} &= 1 - IoU + \rho^2(b, b^{gt})/c^2 + \alpha v
\end{aligned} \tag{5}$$

YOLOv5 loss function. YOLOv5 loss function is essentially same as the YOLOv4 loss function except for the optional focal loss function to replace the the cross entropy loss function in the confidence loss and/or the classification loss.

The focal loss function pays more attention to hard samples. It achieves this goal by using a weighting factor in the cross entropy function. More specifically, the cross entropy function $-\log(p)$ is replaced with $-(1-p)^\gamma \log(p)$, where γ is a weighting factor used to reduces the relative loss for well-classified examples.



Figure 5. Detected faces on the largest selfie image in the world.

B. Qualitative Demonstrations of YOLO5Face

To demonstrate the qualitative effect of YOLO5Face, we show the detected faces on the largest selfie image in the world, shown in Figure 5. At the confidence threshold of 0.2, our YOLOv5m model detects 935 faces. Please note that the confidence scores of different face detectors do not mean the same. At the confidence threshold of 0.2 in our face detector, the false-positive rate is very low.