Simultaneous Person, Face, and Hand Detector Based on Improved YOLOv5

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Abstract—Many human, hand, and face detectors have achieved remarkable achievements in recent years. With the vigorous development of convolutional neural networks, applications based on these detectors were increasingly widely applied in practice. Following this trend, this paper develops a simultaneous human, hand, and face detector based on YOLOv5 network architecture. The research focuses on redesigning the backbone and neck with compact network architectures EfficientNet and CBAM attention mechanism. The proposed network is trained and evaluated on the fine-tuned Human-Parts dataset. As a result, this network reached 87.2% of mAP @0.5 and 58.6% of mAP@0.5:0.95. This result outperforms most of the original YOLOv5 network architectures and is comparable to large-scale YOLOv5 architectures and the latest YOLOv8 architecture.

Index Terms—Attention module, Convolutional Neural Network (CNN), Hand detection, Human detection, Lightweight architecture, Face detection, YOLOv5.

I. INTRODUCTION

The face and hands in the overall human body are very important organs. They perform most human actions to interact with other bodies and the external environment. Many applications have been developed and applied in the fields of computer vision such as Human Action [1], Human-Computer Interaction (HCI) [2], and Human Tracking [3]. In particular, the strong emergence of the convolutional neural network (CNN) with its outstanding advantages over the past decades has released a lot of robust detection algorithms in person detection, face detection, and hand detection. However, the methods only focus on detecting each object individually, ignoring their inherent relationship. This study considers human body, hand, and face detection as a multi-level object detection task [4] to explore more effective object detection in the overall context. It is also consistent with the ability to perform on multi-scale objects of the YOLOv5 network architecture. Therefore, this paper proposes a method to improve the YOLOv5 network for simultaneous detection of body, hand, and face. This technique takes advantage of compact, efficient network architectures such as EfficientNet to optimize network parameters. Besides, the use of the Convolutional Block Attention Module (CBAM) mechanism to guide the network to learn salient informative features. This combination aims to enhance multi-scale object detection and deployment on real-time applications.

The main contributions of this paper are as follows:

- Proposed a simultaneous person, face, and hand Detector based on the YOLOv5 network with lightweight architectures and CAM attention mechanism to optimize the network parameters and detection ability.
- Inspected and fine-tuned the Human-Parts dataset for the YOLO architecture family. This dataset was trained and evaluated with proposed networks, all variants of the YOLOv5, and several lightweight YOLOv8 networks to compare the performance.

The rest of the paper is organized as follows: Section II introduces the methods relative to human, hand, and face detection. Section III explains in detail the proposed method. Section IV summarizes and analyzes the experimental results. Finally, Section V concludes the issue and presents future works.

II. RELATED WORK

This section introduces the related methods applied in human, hand, and face detection. These techniques can be considered with single human part detection and simultaneous human part detection methods.

A. Person detection methods

The pedestrian detection in [5] combined low-level features like CNN, HOG, and Haar with high-level features. MultiContext Cascaded Convolutional Networks (MCCNN) [6] integrated multiple context regions at different scales to effectively capture multi-scale pedestrian features. Fast R-CNN with Context Aggregation Networks (FRCN-CAN) [7] incorporates context information by using context aggregation networks, which gather global scene context to improve pedestrian detection accuracy within the Fast R-CNN framework.

B. Face detection methods

Authors in [8] proposed a face detector based on a bi-channel network and a self-learning method for face detection challenges such as multi-view and occlusion. The study in [9] improved the InceptionV2 network to build a cascaded CNN for detecting small-sized target faces. For low computing devices, FaceBoxes [10] combined the Rapidly Digested
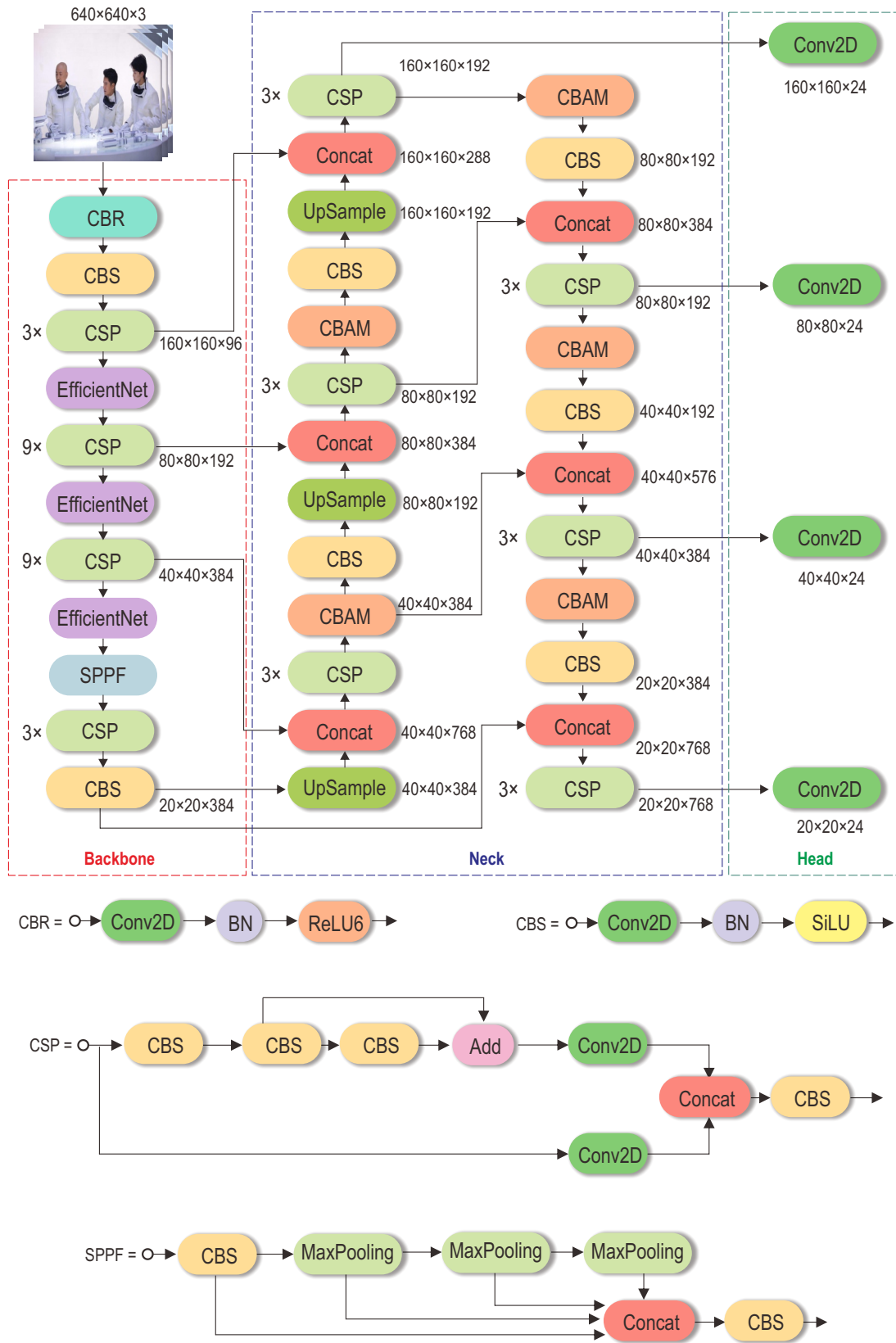
Fig. 1. The overview of the proposed network architecture and submodules.

Convolution Layers and Multiple Scale Convolution Layers in a powerful face detection suite. FlashNet [11] was developed from the MobileNetV2 network and free-anchor mechanism to optimize computation cost. This work [12] designed the lightweight CNN network architecture for an efficient face detector applied in surveillance systems.

C. Hand detection methods

The method in [13] proposes a one-stage CNN network that detects hand position and hand orientation. The Faster-RCNN network was applied in [14] to detect the position of the driver's hand on the steering wheel. A combination of CNN and the hand skin segmentation techniques in [15] to locate the hand position in unconstrained scenarios. The authors in b2 proposed a hand mask and hand orientation detection based on the Mask-CNN network and new attention techniques. [16] also proposed a hand detection reusing CNN and the attention module for robust hand localization ability.

D. Simultaneous human part detection methods

The authors in [17] propose a Detector-in-Detector network (DID-Net) for multi-level object detection which combined a light-weight parts detector after the Faster-RCNN structure to perform human, face, and hand detection. This work also collected a large dataset for this task, named Human-Parts dataset.

III. PROPOSED METHODOLOGY

Fig. 1 shows the overall proposed network architecture. This network is an improvement from YOLOv5 architecture [18] comprised of three modules: backbone, neck, and detection head.

A. Backbone module

The Backbone module utilizes the architecture of the YOLOv5 backbone with some changes and replacements. The Backbone module utilizes the architecture of the YOLOv5 backbone with some changes and replacements. Specifically, it retains the Cross Stage Partial (CSP), Spatial Pyramid Pooling Fast (SPPF) structures and incorporates lightweight blocks such as CBR (Convolution - BN - ReLU6), CBS (Convolution - BN - SiLU), and EfficientNet. In YOLOv5 architecture, the Focus block presents the advantages of feature extraction but it causes computational complexity and network parameters problems. From that observation, this work replaces the Focus block with another straightforward one, named the CBS block. This block is designed based on a convolution layer (1×1 Con2D) followed by a batch normalization (BN) and a ReLU6 activation function. Besides, the CONV block in the original YOLOv5 backbone is also replaced by the CBS block. The structure of CBS is the same as CBR but they are just different at activation function. The activation function in the CBS block is SiLU. The lightweight EfficientNet [19] block is designed quite simply with two convolution (1×1 Conv2D and 3×3 Conv2D) and one depthwise (3×3 DWConv2D) layers, interspersed with a BN and a ReLU6 activation function (for

stride 2 case (Fig. 2 (b)). The same above design is for the stride 1 case (Fig. 2 (a)) but adds a skip connection to aggregate the input feature map with the output feature map of the main branch using the addition operation. Its feature extraction process focuses on the channel dimension. The backbone module generates the multi-level informative feature map for the next module process. The structure of the backbone and sub-blocks are described in Fig. 1
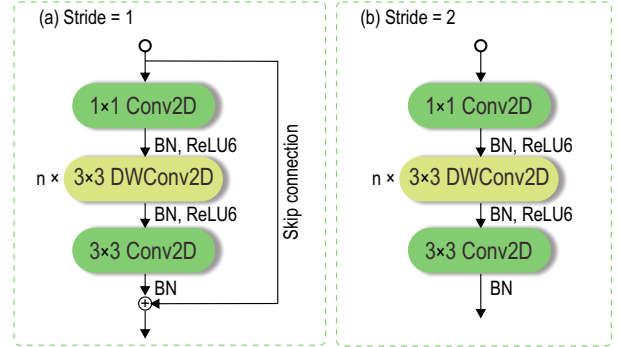

Fig. 2. The lightweight EfficientNet block.

B. Neck module

The Path Aggregation Network (PAN) [20] mechanism is still reused in the proposed neck module. This mechanism merges the current feature maps with previous upsampled feature maps by concatenation operations. In addition, this work adds the CBAM [21] attention block after each CSP block to increase the focusing ability on salient features. The output of the neck module is four aggregated feature maps corresponding to the four scale levels of the object to be detected: large ($20 \times 20 \times 768$), medium ($40 \times 40 \times 384$), small ($80 \times 80 \times 192$), and very small ($160 \times 160 \times 192$). The structure of CBAM is presented in Fig. 3
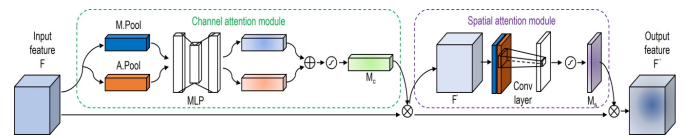

Fig. 3. The structure of CBAM attention block.

C. Detection head module

To build the detection head module, this study reutilizes three feature map levels like YOLOv5 for small, medium, and large object scales and adds one more level for a very small object scale. These four output feature maps go through four convolution operations to produce four detectors with dimensions $160 \times 160 \times 24$, $80 \times 80 \times 24$, $40 \times 40 \times 24$, and $20 \times 20 \times 24$ for very small, small, medium, and large object sizes, respectively. Each detector head uses three anchors of different sizes. Table I shows the details of the detection

head module. The prediction coefficient of each detector is calculated as follows:

$$C = (5 + Class_n) \times Anchor = (5 + 3) \times 3 = 24, \quad (1)$$

where C is the detection coefficient, $Class_n$ is the number of classes, and $Anchor$ is the number of anchors.

Heads	Input	Anchor sizes	Ouput	Object
1	$160 \times 160 \times 192$	(5, 6), (8, 14), (15, 11)	$160 \times 160 \times 24$	Smallest
2	$80 \times 80 \times 192$	(10, 13), (16, 30), (33, 23)	$80 \times 80 \times 24$	Small
3	$40 \times 40 \times 384$	(30, 61), (62, 45), (59, 119)	$40 \times 40 \times 24$	Medium
4	$20 \times 20 \times 768$	(116, 90), (156, 198), (373, 326)	$20 \times 20 \times 24$	Large

Class	Labels	P	R	mAP@0.5	mAP@0.5:0.95
all	14,354	87.9	83.7	87.2	58.6
person	4,796	91.4	78.6	87.7	63.2
face	3,728	89.3	90.8	90.7	63.5
hand	5,830	82.4	81.2	82.9	49.3

D. Loss function

This paper applies the loss function from YOLOv5 which is defined as follows:

$$Loss_{total} = \lambda_{box}Loss_{box} + \lambda_{obj}Loss_{obj} + \lambda_{cls}Loss_{cls}, \quad (2)$$

where $Loss_{box}$ is the bounding box regression loss is computed by using CIoU loss [22]. $Loss_{obj}$ and $Loss_{cls}$ are the object loss and the classification loss, respectively. They use the Binary Cross Entropy loss [23] to calculate. λ_{box}, λ_{obj}, and λ_{cls} are balancing parameters to control the overall loss.

IV. EXPERIMENTS

A. Dataset

The original Human-Parts dataset [17] contains 14,962 images with 10,6879 annotations for three categories: person, hand, and face. The images in this dataset were high-resolution and collected from IA-Challenger. The annotation format followed the PASCAL VOC dataset. During the experiment, this study recognizes that this dataset lost a lot of annotation when convert to YOLO format. Therefore, this work only uses 10,035 images including 8,038 images for training and 1,997 images for evaluation phases.

B. Experimental setup

The proposed network architecture is implemented based on YOLOv5 source code. This network was trained and evaluated on a Testla V100 32GB GPU and tested on another GeForce GTX 1080Ti 11GB GPU. The input image size is 640×640 px. The learning rate is set from 10^{-5} to 10^{-3}. The momentum is also assigned from 0.8 then gradually increases to 0.937. The Adam optimization is used for updating during training.

The training process goes through 200 epochs with a batch size of 32. The balancing parameters are set as $\lambda_{box} = 0.05$, λ_{obj}=1, and $\lambda_{cls} = 0.5$. The training phase applies several data augmentation methods such as mosaic, translate, flip, and scale. The inference time (ms) is implemented and reported with the same training input image size, batch size of 32, confidence threshold and IoU threshold are set to 0.5.

C. Experimental results

The performance of the proposed network is evaluated and compared with all versions of YOLOv5 (n, s, m, l, x) and two versions of YOLOv8 (s, n). These networks are trained from scratch on the Human-Parts dataset. The comparison results are shown in Table III. As a result, the proposed network achieves 87.2% of mAP@0.5 and 58.6% of mAP@0.5:0.95. With the mAP@0.5 metric, the performance of the proposed network is slightly lower than that of YOLOv8s (0.5%↓) and YOLOv5l (0.1%↓) but it is superior to other network architectures. With the mAP@0.5:0.95 metric, the performance of the proposed network is better than that of YOLOv8n (0.2%↑), YOLOv5n (4.9%↑), and YOLOv5s (1.3%↑) and slightly worse than the rest of the networks in YOLOv5 and YOLOv8 families. In terms of speed, the proposed network is faster than the large-size models (YOLOv5l (2.8 ms↑), YOLOv5x (12.9 ms↑)) but it is slower than small-size models (YOLOv5n (8.3 ms↓), YOLOv5s (6.4 ms↓), and YOLOv8n (4.7 ms↓)). Besides, its speed can compare with other model sizes like YOLOv5m and YOLOv8s in acceptable network parameters and computational complexity (GFLOPs). It has promising for application in real-time tracking and surveillance systems. Table II shows the detailed detection results for each class on the Human-Parts validation set. Fig. 4 presents several qualitative results on the Human-Parts dataset with different scenes, human poses, head poses, and hand poses. The comparison results between the proposed network and YOLOv5m in Fig. 5 prove that the proposed network is better than the YOLOv5m network architecture when detecting the hands and faces. For person detection ability, both are the same. From this comparison, it is obvious to see the balance in the person, face, and hand detection of the proposed network with acceptable computation complexity and network parameters. This allows the proposed model can be applied in real-time Human-Robot interaction or human tracking applications. However, this model is still affected by several factors that reduce the detection ability such as overlap, dense, and tiny objects.

D. Ablation study

To evaluate the effectiveness of each block in the proposed network, this experiment conducts several ablation studies. Each block is replaced individually to build the new model and then trained and evaluated on the Human-Parts dataset. The obtained results are described in Table IV. The comparison results demonstrate that the Focus block in YOLOv5 increases the network parameter but the mAP@0.5 and mAP0.5:0.95 reduce by 0.3% and 0.5%, respectively. Using EfficientNet and CBAM blocks had the same effect with mAP@0.5, however,

TABLE III

COMPARISON RESULT OF PROPOSED NETWORK WITH OTHER NETWORKS ON HUMAN-PARTS VALIDATION SET.

Models	Parameter	Weight (MB)	GFLOPs	mAP@0.5	mAP@0.5:0.95	Inf. time (ms)
YOLOv5x	86,186,872	173.1	204	87.2	60.9	22.4
YOLOv5l	46,119,048	92.8	107.8	87.3	60.3	12.3
YOLOv5m	20,861,016	42.2	48.0	86.9	59.3	6.7
YOLOv5s	7,018,216	14.4	15.8	86.7	57.3	3.1
YOLOv5n	1,767,976	3.8	4.2	85.4	53.7	1.2
YOLOv8n	3,006233	6.2	8.1	86.3	58.4	4.8
YOLOv8s	11,126,745	22.5	28.4	87.7	60.7	8.8
Our	**25,655,818**	**52.3**	**82.3**	**87.2**	**58.6**	**9.5**

Inf. time (ms): Inference time is evaluated on a GeForce GTX 1080Ti 11GB GPU.

Fig. 4. The qualitative result on Human-Parts validation set.

mAP@0.5:0.95 large drops (18.7%↓) when the CBAM block is ignored. Adding a detector can increase the network parameters by two times but increase both mAP measurements. Finally, when comparing SPP and SPPF blocks, SPPF is better at mAP@0.5:0.95 (0.3%↑). From the above analysis, this research selects the last architecture to design the human, face, and hand detector. Therefore, this work selects the last architecture to train, evaluate, and report on vehicle detection capabilities.

TABLE IV

ABLATION STUDIES WITH THE DIFFERENT MODULES IN THE PROPOSED NETWORK ON THE HUMAN-PARTS VALIDATION SET.

Modules	Networks					
CBR	Focus	✓	✓	✓	✓	✓
EfficientNet	✓					
SPPF	✓	✓	✓	✓		✓
SPP					✓	
CBAM	✓	✓		✓	✓	✓
P2		✓	✓	✓	✓	✓
Parameter	25,659,658	22,117,210	22,113,370	10,904,160	25,655,818	25,655,818
Weight (MB)	87.5	45.1	45.1	22.3	52.3	52.3
GFLOPs	83.0	73.6	72.8	21.2	82.3	82.3
mAP@0.5	86.9	86.6	86.8	84.8	87.2	87.2
mAP@0.5:0.95	58.1	58.0	39.3	54.5	58.3	58.6

Fig. 5. The comparison result between proposed method and YOLOv5m on Human-Parts validation set.

V. Conclusion and future work

This paper proposes a technique to improve the YOLOv5 architecture network for simultaneous human, face, and hand detection. Research concerns redesigning backbone and neck modules using a combination of lightweight architectures EfficientNet and CBAM attention mechanism. On the other hand, this work refines and distillates the images with the correct annotation for the YOLO architecture training task. With the optimization of network parameters, computational complexity, inference speed, and small-size object detection ability, the proposed network has the potential to be deployed on low-computing devices. In the future, the detector will be developed with other novel attention mechanisms to boost small-size object detection.

Acknowledgement

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