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An improved YOLOv5 for real-time human detection in infrared images

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ABSTRACT

The recent prominence of using infrared technology for human detection has garnered attention, particularly for applications in intelligent video surveillance and self-driving systems. This technology offers advantages in adverse weather conditions and night vision. However, within deep learning, the challenge of variable illumination during human detection persists. This study presents a novel method for identifying individuals in thermal images by enhancing the you only look once (YOLOv5s) algorithm. The approach incorporates the Bi-directional feature pyramid network (BiFPN) and the convolutional block attention module (CBAM) to improve the model's feature integration and extraction capabilities. Evaluation on established thermal imaging datasets confirms the method's superiority over state-of-the-art convolutional neural networks (CNN) based techniques, achieving remarkable precision 99.1% and recall 96.9%.

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1. INTRODUCTION

Human identification stands as a central theme within the realm of computer vision investigation, specifically within fields like surveillance applications and the intelligent transport sector. In contrast to traditional red, green and blue (RGB) cameras, thermal infrared cameras demonstrate heightened resilience against specific challenges encountered in real-time scenarios, like adverse weather or nocturnal settings [1]. Detection of individuals in thermal imagery is achieved by leveraging temperature variance inherent in the visual data. Nonetheless, disparities exist between thermal and RGB images, encompassing factors such as diminished resolution, amplified noise, and a restricted dynamic range.

Recently, thanks to the advent of deep learning, various detection models with robust detection abilities have evolved. As detection methods have shown great results on visible images, many researchers have improved these methods and applied them to infrared imagery. But this is still a very complex task because of the low resolution of thermal images compared to optical images.

Prior studies concerning the identification of humans in thermal images can be categorized into two groups: approaches that utilize manually designed attributes and those relying on learned features. Techniques relying on manually designed attributes involve training a supervised machine learning model on predetermined features using labeled training data. For instance, in references [2], [3], human detection is achieved by employing a support vector machine (SVM) classifier trained on histograms of oriented gradients (HOG). The preprocessed thermal images are then used to extract features, with preprocessing involving noise reduction and contrast enhancement. A comparable approach in Riaz *et al.* [4] replaces HOG with census transform histogram, the experimental findings demonstrate that centrist outperforms HOG in terms of detection accuracy, while also significantly reducing both training and testing time. Zhou *et al.* [5] in their study, proposed a thorough approach to detect pedestrians in infrared images, utilizing a centripetal model based on head saliency and a fusion mechanism that combines global and local information. Experimental results indicate that the algorithm successfully extracts pedestrians in various motion patterns and complex environments, showcasing its robustness and adaptability. Teutsch *et al.* [6] developed a holistic approach that involves identifying maximally stable extremal region (MSER) hot spots, classifying them using a DCT-based descriptor and an adapted random naïve bayes (RNB) classifier. This method successfully achieves high detection rates in real-time across various low-resolution videos in different long-wave-infrared (LWIR) datasets. The detection of human motion in thermal video is addressed in [7] using a fisher's ratio-based background subtraction method, the proposed method is highly perceptual, robust, and possesses a discriminative capability.

Recently, convolutional neural networks (CNNs) have found utility in fully automating the process of learning and extracting features for techniques that detect humans, relying on acquired knowledge. In a recent publication [8], an approach involving CNNs and visible light cameras was introduced to identify humans during nighttime. The outcomes highlighted that instances of wrongly identifying or missing humans were confined to images captured under extremely low-light circumstances, making it challenging to differentiate human shapes even through direct observation. Similarly, a similar method was suggested in [9] to recognize passengers on roads using near-infrared cameras. The findings demonstrated that by refining the CNN model and incorporating self-learning softmax, a commendable level of accuracy was achieved, signifying its potential in recognizing pedestrians promptly and accurately in real-world scenarios.

To enhance automatic person detection from thermal images, researchers utilized you only look once (YOLO) [10]. Ivašić-Kos *et al.* [11] conducted experiments using the YOLO neural network in its default configuration and also after training it on a subset of their custom dataset of thermal videos. The experimental results demonstrated a notable enhancement in the performance of human detection in thermal imaging when using the trained YOLO model compared to the original model. Huda *et al.* [12] nine distinct phenomena within the dataset were identified and investigated for their impact on model adaptation in transfer learning. Encouraging outcomes from the tests validate the study's findings and highlight its importance. Kristo *et al.* [13] focuses on automatic person detection in thermal images by utilizing convolutional neural network models designed for red, RGB image detection. During the experiments, YOLOv3 demonstrated superior speed compared to other detectors while maintaining comparable performance. Khalfaoui *et al.* [14] evaluates the performance of YOLO algorithms for person detection, specifically YOLOv3 and YOLOv5. The experimental results show that YOLOv3 is faster in processing compared to YOLOv5, while YOLOv5 achieves higher recognition accuracy.

However, most methods for human detection from thermal images relying on hand-crafted features are not adaptable to thermal signatures and the diverse range of environmental circumstances. In addition to being computationally expensive, CNN models created for RGB images also fall short of offering appropriate detection capability for low-resolution and low-power thermal signatures with complicated backgrounds. Consequently, the major challenge is designing a cheap, computationally efficient technique that can deliver high performance for varying thermal signatures and environmental circumstances. However, it is difficult to directly employ object detection techniques, such as YOLOv5, to identify people from real infrared images. The complex nature of the real environment means that unavoidable elements like light variations, low contrast, visibility, high noise, and occlusion will impact images taken by even the most sophisticated cameras.

In response to these obstacles, this article suggests an enhanced YOLOv5s model tailored for detecting humans in infrared conditions within practical settings. This enhancement is accomplished by merging the convolutional block attention module (CBAM) attention module into the backbone of YOLOv5s and adopting the Bi-directional feature pyramid network (BiFPN) structure in lieu of the initial feature fusion arrangement. The organization of this manuscript is partitioned into four segments: starting with an introductory first section, followed by an elaboration of the proposed methodology in the subsequent part. The third section showcases the outcomes of experiments and discussion, succeeded by a concise conclusion and an outline of future prospects, encapsulating the essence of our study.

2. METHOD

2.1. YOLOv5s

The YOLO series of algorithms, such as YOLOv5 [15]-[17], is among the most widely used deep learning algorithms. These algorithms employ an end-to-end fully convolutional neural network for object detection, directly generating the target classes and bounding boxes. YOLO algorithms belong to the one-stage family of detection algorithms, which are preferred in practical applications due to their simpler network architecture, fewer parameters, and faster detection rate compared to two-stage models.

YOLOv5 is considered one of the best one-stage detection algorithms. It consists of three core components: the backbone, the neck, and the head. The backbone is used initially to extract visual features for detection or classification tasks. The neck combines features from different levels produced by the backbone to enhance the model’s ability to handle changes in target scale. Lastly, the head generates the bounding box and class category of the object. YOLOv5 utilizes CSPDarkNet53 as its backbone, which integrates the cross stage partial network (CSPNet) [18] to minimize redundant gradient information and reduce repetitive calculations. CSPNet enables the transmission of gradient information through multiple network pathways. The neck, path aggregation network (PANet) [19], employs top-down and bottom-up paths to merge features from various layers, enhancing the model’s ability to detect objects at different scales. The prediction results are produced by the multi-scale detection head, which consists of three branches capable of identifying objects of varying sizes. The architecture of YOLOv5 is depicted in Figure 1 [20].

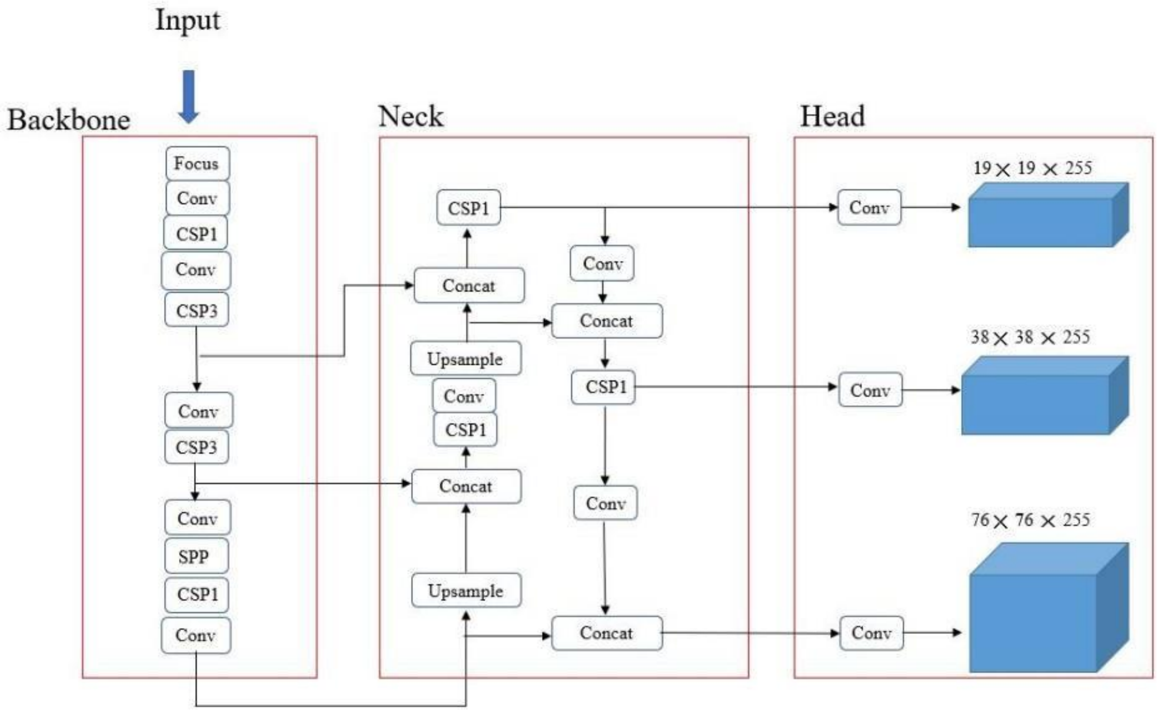


Figure 1. The architecture of YOLOv5

2.2. Bi-directional feature pyramid network

Object detection models have been focused on efficiently representing and handling multi-scale features as feature fusion can lead to more discriminative features. To enhance the performance of object detection models, it is crucial to understand how to effectively fuse high and low-level features. The YOLOv5 model utilizes the feature pyramid network (FPN) and pyramid attention network (PAN) architectures for multi-scale feature fusion. FPN combines multi-scale features through a top-down approach, but it is limited by the one-way flow of information. PAN addresses this limitation by incorporating a bottom-up path aggregation network on top of FPN, but it requires additional calculations and parameters compared to FPN. To overcome these limitations, Tan *et al.* [21] proposed a BiFPN structure based on the PAN architecture, which is why we have chosen it as the feature fusion structure for YOLOv5.

According to Figure 2, PAN in Figure 2(a) modified BiFPN in Figure 2(b) in three key ways. Firstly, it eliminates nodes with only one input edge to simplify the fusion of different features. Secondly, in order to increase the number of fused features, it adds an edge between input and output nodes that are on the same level without incurring excessive costs. Finally, BiFPN treats each bidirectional connection as a feature network layer, enabling higher-level feature fusion. This is in contrast to PAN, which only has one bottom-up and one top-down path.

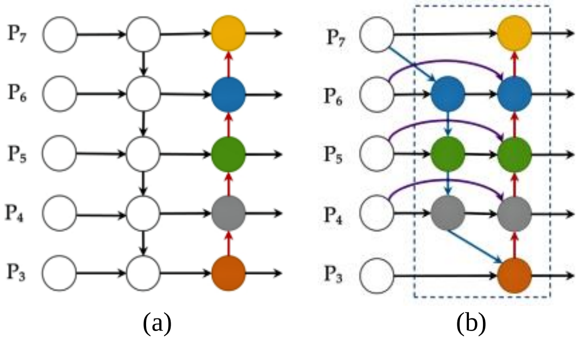


Figure 2. Feature fusion structure: (a) PAN and (b) BiFPN

2.3. Convolutional block attention module

In real-world scenarios, the complex environment and the intrinsic features of human's present challenges for the detection task. The environment's complexity arises from factors such as low visibility, blurriness, high noise, and low illumination backgrounds. All these factors contribute to the increased difficulty of the detection task. Recently, attention mechanisms have been integrated into neural networks and employed in various computer vision applications. CBAM is a lightweight attention mechanism that sequentially combines spatial attention with channel attention. It consists of two separate submodules: the channel attention module (CAM) and the spatial attention module (SAM), which control channel and spatial attention, respectively, as shown in Figure 3 [22]. In our approach, we incorporate the CBAM module after the focus structure of the backbone network for the object detection task. This integration aims to enhance object localization accuracy and reduce the issue of object aggregation by augmenting key spatial and channel properties in the feature map.

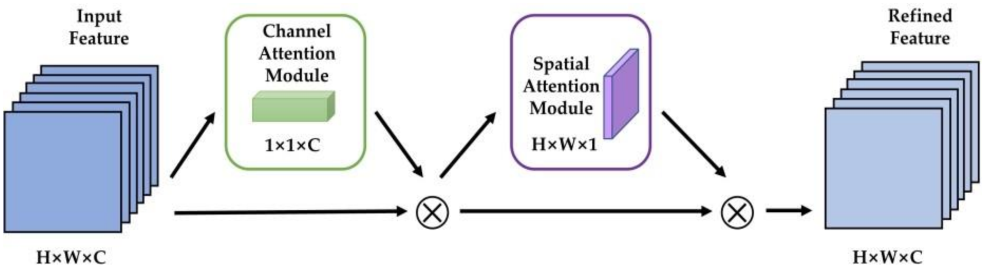


Figure 3. The CBAM overview

3. RESULTS AND DISCUSSION

In order to assess the efficacy of the proposed approach, a consolidation of two distinct thermal image datasets was undertaken. The initial dataset is denoted as the autonomous system lab thermal infrared dataset (ASL-TID), encompassing a collection of 3,837 thermal images depicting human subjects [23]. The secondary dataset, known as the Ohio State University Thermal Pedestrian Dataset (OSU), contributes an additional 284 thermal images originating from ten distinct image sequences. These sequences were captured across diverse weather and humidity conditions [24]. The cumulative size of the amalgamated dataset is detailed in Table 1. Notably, both datasets comprise aerial thermal images obtained from an aerial perspective, akin to those captured by unmanned aerial vehicles (UAVs). The final dataset was partitioned into three subsets: 70% allocated for training, 20% for validation, and the remaining 10% designated for testing purposes. The distribution of these subsets is illustrated in Figure 4, which showcases sample thermal images extracted from both datasets. In the evaluation of our model's performance, precision, recall, and mean average precision (mAP) were utilized as gauges, adhering to the formulations;

$$P = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{1}$$

$$R = \frac{TP}{TP+FN} \tag{2}$$

$$mAP = \frac{1}{C}\sum_{K=i}^{N} P(K)\Delta R(K) \quad (3)$$

where true positives (TP) represent the number of positive samples correctly classified as positive. False positives (FP) represent the number of negative samples incorrectly classified as positive. False negatives (FN) refer to the number of positive samples misclassified as negative. C represents the number of object categories. K is the intersection over union (IOU) threshold. P(k) represents precision at IOU threshold k. R(k) represents recall at IOU threshold k. N is the number of IOU thresholds.

Table 1. Prepared dataset

Dataset number	Prepared dataset	Total samples
1	OSU	284
2	ASL-TID	3,837
3	Combined dataset	4,121

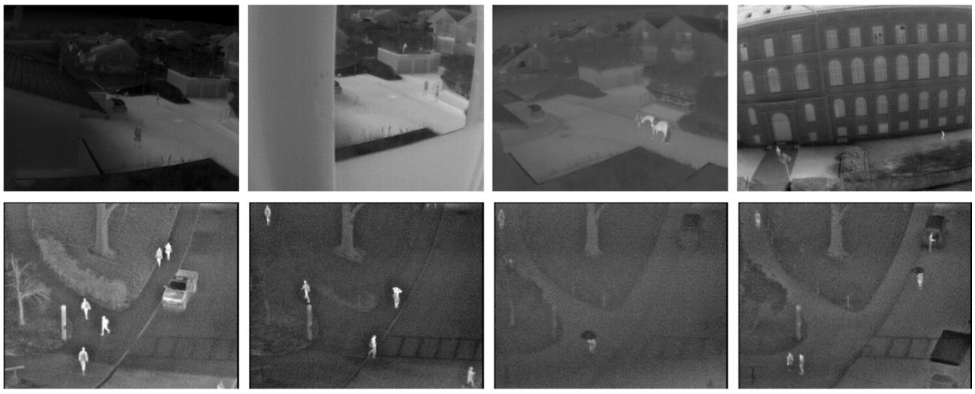


Figure 4. Sample images from the ASL-TID (top row) and OSU pedestrian (bottom row) thermal image datasets

The utilization of YOLOv5s [25] has been made accessible through GitHub and was crafted using the Python programming language. The training procedure was executed on a Linux operating system encompassing CUDA 11.1, PyTorch 1.12.1, Python 3.7, and an NVIDIA Tesla T4 graphics card. Renowned for its streamlined architecture and swift computational capabilities, YOLOv5s is recognized as a real-time object detection algorithm. Within the context of this research, an advanced iteration of the YOLOv5s model was adopted for the purpose of detecting human individuals within infrared images. As evidenced by the findings presented in Table 2, the model showcased an impressive precision level of 98.80%, recall rate of 96.30%, and a mAP score of 98.70% on the validation dataset.

The graphs in Figure 5 illustrate the progress of our model over 100 epochs and present key metrics for both the training and validation sets. They depict two types of loss: objectness loss and box loss. The box loss assesses the model’s ability to accurately encompass an object within the predicted bounding box and determine the object’s center with precision. On the other hand, the objectness loss measures the probability of an object’s presence within a proposed area of interest.

Table 2. The validation results of the proposed method

Variable	Precision (%)	Recall (%)	mAP (%)
Our method	98.80	96.30	98.70

The enhanced model was also compared to other models using the same infrared human detection dataset, and the detection results are presented in Table 3. In this study, the modified YOLOv5s model achieved the highest mAP value, which was 2.07% higher than the original YOLOv5s network, and 12.19% and 14.32% higher than the YOLOv4 and EfficientDet-D0 networks, respectively. This clearly demonstrates that the combination of YOLOv5s with the CBAM attention module and BiFPN feature map fusion structure can effectively extract more accurate features and achieve advanced feature fusion.

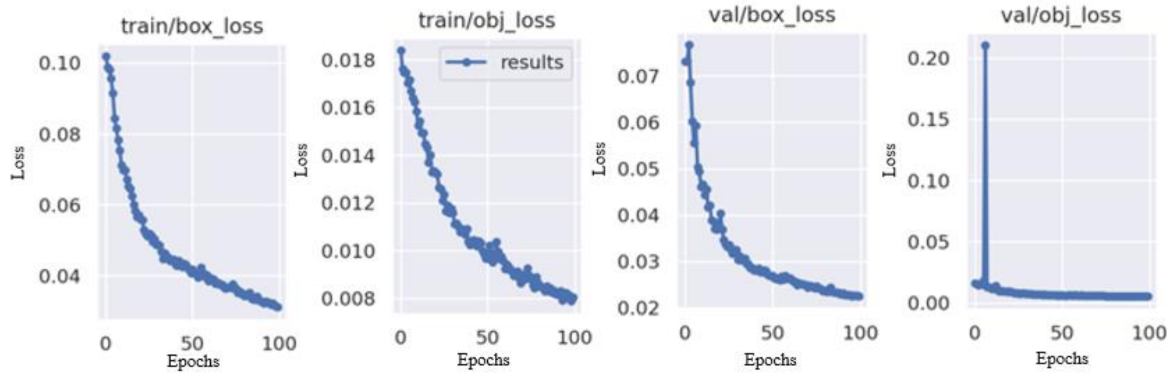


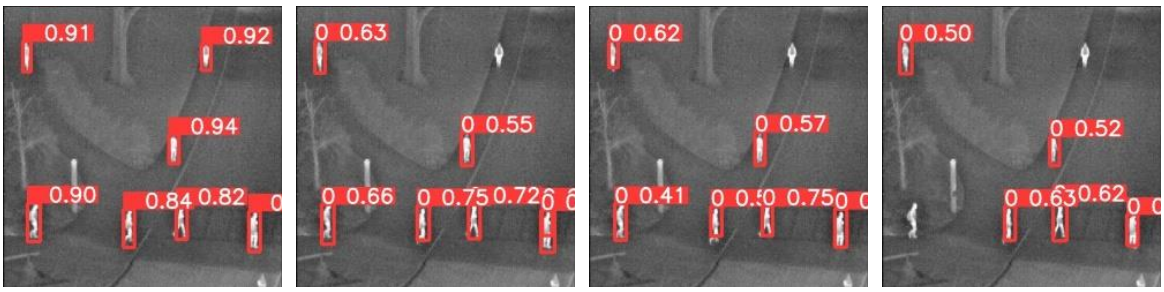
Figure 5. Box loss and objectness loss for the training and validation sets

The modified YOLOv5s model also surpassed the other models in terms of recognition accuracy and recall, achieving 98.30% and 96.90%, respectively. Both the YOLOv5s network and the EfficientDet-D0 network are lightweight with model sizes of 14.30 MB and 15.13 MB respectively. Nevertheless, by integrating the CBAM module alongside the BiFPN feature fusion configuration into the YOLOv5s architecture, the model's dimensions merely expanded by a marginal 1.52 MB when compared to the original YOLOv5s framework. As demonstrated in Table 3, the network introduced in this study not only demonstrated superior recognition accuracy over alternative models but also adeptly preserved the lightweight attributes intrinsic to the initial YOLOv5s network. Based on the empirical findings, it can be deduced that the combination of the CBAM attention module with the BiFPN structure notably amplifies the performance of the detection model.

The results of the detection for each method on the test set are presented in Figure 6. It is noticeable that in YOLOv5, YOLOv5s-CBAM, and YOLOv5s-BiFPN, there were instances where some individuals were missed and not detected. However, our method demonstrated the best results. Therefore, based on the experimental outcomes, it is evident that incorporating the CBAM and BiFPN modules in YOLOv5s can greatly enhance the model's recognition accuracy.

Table 3. Comparison of the proposed method with other methods using the same dataset

Methods	Precision (%)	Recall (%)	mAP (%)	Model size (MB)
EfficientDet-D_0	81.89	78.17	84.78	15.13
YOLOv4	83.37	81.66	86.91	31.22
YOLOv5s	95.34	90.27	97.03	14.30
YOLOv5s-CBAM	95.60	94.05	98.02	14.50
YOLOv5s-BiFPN	95.08	94.79	98.28	15.81
Our method	98.30	96.90	99.10	15.82



Our network YOLOv5s-BiFPN YOLOv5s-CBAM YOLOv5s

Figure 6. Sample detection results for the test set

4. CONCLUSION

This research employs advanced deep learning techniques to detect individuals in infrared images. The original feature fusion architecture (FPN+PAN) is replaced with the BiFPN structure, enhancing the model's feature integration. Furthermore, the CBAM attention module is incorporated into the YOLOv5s backbone, enhancing feature extraction. The improved model shows significant increases in precision (2.96%)

and mean average precision (2.07%) compared to the original YOLOv5s. The algorithm achieves rapid image detection (around 0.01 seconds on a Tesla T4 GPU) for real-time applications. The model is robust to various weather conditions and offers an effective solution for infrared human detection. Notably, the approach minimizes computational overhead, making it suitable for thermal-based air surveillance or drone-assisted monitoring. Future research will focus on optimizing the method for embedded devices, using larger thermal and visible datasets, and implementing it in different domains to identify potential security threats and monitor activity in sensitive areas such as airports, military installations, and border crossings.

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