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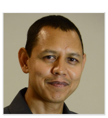

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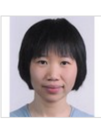


L. Rong, PhD

Aarhus University, Aarhus, Denmark

Nanik Suciati
Department of Informatics, Faculty of Intelligent Electrical and Informatics Technology
Institut Teknologi Sepuluh Nopember
Jl. Raya ITS, Surabaya, 60111, Indonesia
nanik@if.its.ac.id

Prof. Dr. John Schueller
Editor-in-Chief
Computers and Electronics in Agriculture

October 25, 2021

Dear Prof. Schueller:

I am pleased to submit an original research article entitled "Yolov4-tiny with Wing Convolution Layer for Detecting Fish Body Part" by Eko Prasetyo, Chastine Fatichah, and Nanik Suciati for consideration to be published in the Computers and Electronics in Agriculture. We previously uncovered a role for wing convolutional layer (WCL), tiny spatial pyramid pooling (Tiny-SPP), bottleneck and expansion convolution (BEC), and an extra-branch as a third-scale detector to enhance detection accuracy of Yolov4-tiny in detection fish body part.

In this manuscript, we show that our proposed model achieves mAP of 92.38% and outperforms the original and other modified Yolov4-tiny models.

We believe that this manuscript is appropriate for publication by the Computers and Electronics in Agriculture because it is related to development and application of computer software, for solving problems in agriculture. Our manuscript creates a paradigm for future studies of the CNN-based approach for object detection with a small model size and high performance.

This manuscript has not been published and is not under consideration for publication elsewhere. We also have no conflicts of interest to disclose.

Thank you for your consideration!

Sincerely,

Nanik Suciati
Department of Informatics, Faculty of Intelligent Electrical and Informatics Technology
Institut Teknologi Sepuluh Nopember

(COMPAG-D-21-02878) Response Letter:

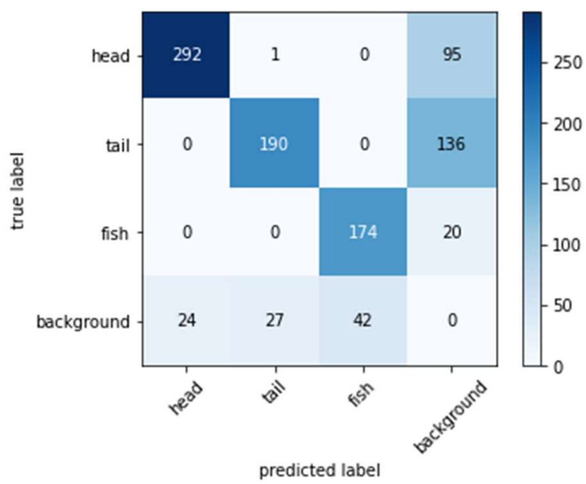
Yolov4-tiny with Wing Convolution Layer for Detecting Fish Body Part

<u>Reviewer #1 comment to the authors:</u>

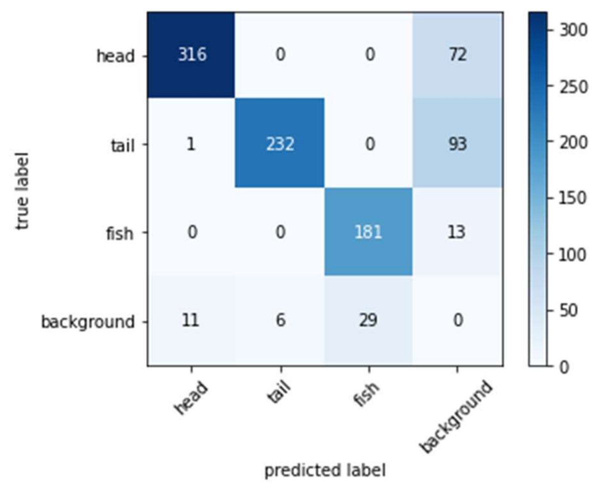
[1] It will be better if we can see the confusion matrix both Yolov4-tiny model and modified Yolov4-tiny model. In fact, I am not fully satisfied with Table 2.

<u>Answer:</u>
Thank you for your valuable comment.

1. We added subsection 4.5 to show the confusion matrix of both the Yolov4-tiny model and the modified Yolov4-tiny model. We also analyze the results achieved in the matrix. The results of the confusion matrix as we show below.



(a) Yolov4-tiny original



(b) WCL-Yolov4-tiny

2. We use the representation of four classes: head, tail, fish, and background. We utilize the background class as a label for other objects that are misdetected. The main diagonal present the true positive result, while the other cells are false positive and false negative. ………………………………………………………………………………… red font, line 472-487

<u>Reviewer #1 comment to the authors:</u>

[2] Please shows some failure cases with proper reasoning.

<u>Answer:</u>
Thank you for your valuable comment.

1. We got false detection in 4 out of 120 testing images during the experiment. We present the image in Fig. 12 and Fig. 11(c) along with an explanation of the reasons as follows:
   The proposed WCL-Yolov4-tiny achieved a significant improvement in object detection. The tail detection performance as a small object increased true positives while decreasing false positives. False positives detected in this case are background or intact fish whose parts are not observable, for example, intact fish with head covered by other objects; and the model detects them as intact fish, as shown by Fig. 12 (a). One fish was detected with 0.56 confidence. Notwithstanding achieving fairly good confidence, the object should not be detected due to an incomplete body part. Another failed case is Fig. 12 (b), the model detected the background as fish with 0.27 confidence. This background should not be detected, and we can ignore it by increasing the confidence threshold. However, increasing the confidence threshold also reduced the true positives achieved. For example, tail and fish with 0.26 and 0.28 confidence, respectively (Fig. 12(a)), are dismissed if the confidence threshold increases to 0.3. Hence, by holding a confidence threshold of 0.25, we achieved more true positive objects with fewer false-positive ones. Another case of misdetection is Fig. 12(c), where a tail with 0.54 confidence should not be detected as a tail. This body part is a fin with an appearance looking like a tail. The similarity of the visual appearance caused the failure of detection by our proposed model. Some detection failures in this model are nevertheless an understandable problem due to natural causes and parameter trade-offs used during the experiment. The number of failures is slight because only four of the 120 test images were detected incorrectly.
   ……………………………………………………………………………… red font, line 544-560

Reviewer #1 comment to the authors:

[3] Figure captions should be little bit expanded to keep the figures stand-alone.

Answer:
Thank you for your valuable comment.

1. We have detailed the figure caption in Fig. 7 and Fig. 10 as follows:
   a. Fig. 7 Sample images of the FFPD dataset. (a). Single fish, (b) Multi fish, (c)-(d) Complicated fish ………………………………………………... red font, line 330
   b. Fig. 11 Visual comparison between (a) Ground truth and fish detection results using: (b) Yolov4-tiny model; (c) WCL-Yolov4-tiny model.. ………………… red font, line 544

Reviewer #1 comment to the authors:

[4] The author shows the itemize contributions. It is good. But too much explanation (i.e. exaggerate explanation) along with itemize contributions is unnecessary. Therefore, I suggest to modify it.

Answer:

Thank you for your valuable comment.

1. We have corrected the contribution explanation in the introduction so that there are not too many explanations as follows:
    a. Replacing the explanation of :
    Yolov4-tiny is a fast object detector that has a small model size and limited performance. Its limited performance is caused by the lack of feature diversity generated by the backbone due to its shallow architecture, in which it only has three CSPDarknet and few convolution layers. This study enhances the diversity of features generated by the backbone using WCL. WCL is a convolution block that is separate and parallel to the main backbone and has more convolutional layers than the main backbone. WCL is employed to support the enhancement of feature diversity by combining itself with the feature map generated by the main backbone at the end of the backbone layer. The use of WCL is expected to improve the detection of whole fish, fish heads, and fish tails.
    with:
    Yolov4-tiny is a fast object detector with small-sized model and limited performance. It is caused by the lack of feature diversity by shallow CSPDarknet. We address such a problem by enhancing the variety of the features using WCL, while by separating and paralleling convolutional layers to the main backbone. The end feature map of WCL is combined with the feature map generated by the main backbones. This way improves the detection of intact fish, fish heads, and fishtails.
    ………………………………………………………………………… red font, line 82-86
    b. Replacing the explanation of :
    SPP is powerful in expanding the diversity of features, however, it has the potential to cause excessive diversity of features. We lower the possibility of this by reducing the kernel pooling used to balance the diversity of features within feature maps.
    with:
    The increase in feature diversity by SPP induces exaggerated features as well. We address this problem by reducing the kernel pooling to balance the diversity of features.
    ………………………………………………………………………… red font, line 88-89
    c. Replacing the explanation of :
    In the detection of whole fish, fish heads, and fish tails, the objects that are being detected vary in size. The first-scale and second-scale detectors are sufficient to detect whole fish and fish heads, while the detection of fish tails requires a third-scale detector due to their small size. We propose the addition of a third-scale detector using an FPN. The feature map of the second-scale is up-sampled and is subsequently combined with the feature map of the skip connection in the backbone that contains features of the third-scale (features of small objects). The third-scale detector helps to detect fish tails that are small and hard to detect using the original Yolov4-tiny.
    with:
    The first- and second-scale detectors of Yolov4-tiny are sufficient to detect intact fish and fish heads. However, it is insufficient to detect fishtails because of the small size. We attach a third-scale detector using a feature pyramid network (FPN) by upsampling the

second scale's feature map which is then combined with the feature map from the previous layer.

……………………………………………………………………… red font, line 91-94

d. Replacing the explanation of :

The third version of Yolo reuses the feature maps of different scales using FPN (Lin et al., 2017). The merging of the first-scale and second-scale feature maps results in the excessive usage of computational resource due to the concatenation of features. We propose a bottleneck and expansion convolution (BEC) using a two-step convolution with a bottleneck and expansion of feature maps. BEC convolutes the concatenation of two feature maps with a lower cost on the same feature map size compared to the standard convolution.

with:

Since the third version, Yolo has used FPN to facilitate multi-scale detectors by concatenating current and previous feature maps and standard convolution. This method causes excessive computational resources. We propose a bottleneck and expansion convolution (BEC) using a bottleneck and expansion convolution sequentially. BEC convolutes the feature maps concatenation using a lower cost than the standard convolution.

……………………………………………………………………… red font, line 96-100

e. Replacing the explanation of :

We propose an enhancement of the Yolov4-tiny model by modifying the backbone of the model, adding Tiny-SPP, replacing the convolution in the FPN connection using BEC, and adding a third-scale detector. We modified the backbone by adding a WCL as a separate convolution layer that is parallel to the main backbone to enhance the diversity of features within the feature maps. The third-scale detector is utilized to increase the ability of the model to detect small objects, in particular fish tails. Tiny-SPP is employed to expand the diversity of features while also preventing excessive diversity of features. BEC is utilized to collect relevant features with a low computational costs. These enhancements can improve and optimize the performance of the Yolov4-tiny model in detecting whole fish, fish heads, and fish tails.

with:

We propose enhancing the Yolov4-tiny model by modifying the backbone using WCL, adding Tiny-SPP, replacing the FPN connection convolution method using BEC, and attaching a third-scale detector. WCL enhances the diversity of features from backbones. Tiny-SPP intention balances and prevents the expansion and excessive diversity of features. BEC collects relevant features with a low computational cost, and the third-scale detector increases the ability to detect small objects, particularly fishtails. These enhancements can improve and optimize the performance of the Yolov4-tiny model in detecting intact fish, fish heads, and fishtails.

……………………………………………………………………… red font, line 102-108

<u>Reviewer #1 comment to the authors:</u>

[5] English needs little bit editing for enhanced readability.

Answer:
Thank you for your valuable comment.

1. We have proofread to refine English for enhanced readability. Proofreading is conducted on this manuscript with 8,446 words. Examples of proofreading results are as follows (*red font*):
    a. A vision system for the classification of fish freshness requires observing the visual appearance of the whole body of a fish or its body parts, such as eyes, head, skin, and tail.
    replaced by
    Detection of a fish's eye, tail and body is the initial process in the vision system for determining the freshness and species of fish, as well as calculating the number of fish automatically in the fishing industry.
    ……………………………………………………………………… Line 12-13
    b. However, massive siltation of the convolution layer in the Yolov4-tiny backbone leads to low feature diversity of the backbone.
    replaced by
    However, massive siltation of convolution layer in the Yolov4-tiny backbone leads to low feature diversity.
    ……………………………………………………………………… Line 16-17
    c. Fish is a dish that is highly nutritious (Jose et al., 2021), and contains proteins, vitamins, and minerals required for human health (Erasmus et al., 2021; Prabhakar et al., 2020).
    replaced by
    Fish is a highly nutritious dish (Jose et al., 2021), and contains proteins, vitamins, and minerals required for human health (Erasmus et al., 2021; Prabhakar et al., 2020).
    ……………………………………………………………………… Line 34-35
    d. Research in segmenting whole fish also conducted to separate fish from complex backgounds using blob analysis (Prados et al., 2017), whole fih detection using description of multiscale deformable fish body combinations (Nian et al., 2017), and Hough circle detection (C. Yu et al., 2020). These approach are commonly experienced by analyzing intensity, color, and shape; the experimenting methods are also impacted by the background, color, and lighting.
    replaced by
    Furthermore, several segmentation methods to separate intact fish from complex backgrounds have been proposed, such as using blob analysis (Prados et al., 2017), combination of multiscale deformable (Nian et al., 2017), and Hough circle detection (C. Yu et al., 2020). These approach are commonly performed by analyzing the intensity, color, and shape of the fish image; which should take into consideration the variations in background, color, and lighting.
    ……………………………………………………………………… Line 55-60
    e. The deep learning approaches for fish detection and localization are also continuously being explored due to higher performance and more robust in complex backgrounds (Sung et al., 2017), more robust in cloudy water conditions (Christensen et al., 2018),

and higher performance in detecting dead fish on water surface (G. Yu et al., 2020). The improved performance is achieved by enhancing the architectural components of the models and by combining them with conventional methods and data enhancement.

replaced by

Meanwhile, several studies have explored deep learning approaches to detect fish and reported better performance than conventional approaches in environments with complex backgrounds (Sung et al., 2017), cloudy water conditions (Christensen et al., 2018), and in the case of detecting dead fish on the water surface (G. Yu et al., 2020). Performance improvements in deep learning approaches are generally achieved by modifying the architecture, combining the architecture with conventional methods and improving data quality.

…………………………………………………………………… Line 61-66

and etc.

<u>Reviewer #1 comment to the authors:</u>

[6] A note on practicability of commercial fish processing application may enhance the paper.

<u>Answer:</u>
Thank you for your valuable comment.

1. We add an explanation of the practicability of commercial fish processing application as follows:

   In section discussion:

   Commercial fish packaging companies require a lightweight, fast, and high-performance processing machine in sorting the freshness of fish; this model supports the requirement in determining the position of fish and body parts. The personal users of mobile applications with limited storage and computation resources also require a simple and low computational resource system to localize mixed fish in one bucket and their freshness level.

   …………………………………………………………………… red font, line 536-541

   In section conclusions:

   The proposed model is lightweight, high-performance, and requires a low computational resource. Hence, it is applicable in mobile devices with limited storage and computational resource in detecting fish and body part localization. Therefore, it can be applied to personal users and the commercial fishing industry.

   …………………………………………………………………… red font, line 571-576

Ubhara Surabaya

Eko Prasetyo <eko@ubhara.ac.id>

Decision on submission to Computers and Electronics in Agriculture

1 message

Computers and Electronics in Agriculture <em@editorialmanager.com> 30 April 2022 at 11:41
Reply-To: Computers and Electronics in Agriculture <support@elsevier.com>
To: Eko Prasetyo <eko@ubhara.ac.id>

Ref.: Ms. No. COMPAG-D-21-02878R1
Yolov4-tiny with Wing Convolution Layer for Detecting Fish Body Part
Computers and Electronics in Agriculture

Dear Mr Prasetyo,

I am pleased to inform you that your paper has now been accepted for publication. My own comments as well as any reviewer comments are appended to the end of this letter.

Your accepted manuscript will now be transferred to our production department. We will create a proof which you will be asked to check. You can read more about this here:

Meanwhile, you will be asked to complete a number of online forms required for publication. If we need additional information from you during the production process, we will contact you directly.

Thank you for submitting your work to Computers and Electronics in Agriculture. We hope you consider us again for future submissions.

Kind regards,
Yanbo Huang
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