Bulletin of Networking, Computing, Systems, and Software – www.bncss.org, ISSN 2186-5140
Volume 14, Number 1, pages 34–35, January 2025

A Lightweight Approach to Defect and Foreign Matter Detection in Children's Snacks Using YOLOv8 with Ghost and ECA Modules

Gukjin Son
ICT Research Institute
DGIST
Daegu, Korea
sudopop@dgist.ac.kr

Howon Yoon
ICT Research Institute
DGIST
Daegu, Korea
howon98@dgist.ac.kr

Youngduk Kim*
ICT Research Institute
DGIST
Daegu, Korea
ydkim@dgist.ac.kr

***Abstract*— In this paper, we propose an efficient object detection approach to identify defects and foreign matters in children's snacks. To achieve both computational efficiency and high accuracy, the proposed model was enhanced with the Ghost module and Efficient Channel Attention (ECA) module. To reduce the parameter count and computational load, the Ghost module is applied to the backbone network. The ECA module compensates for potential accuracy losses by emphasizing important channel features. Our private dataset was used to evaluate the model. Experimental results demonstrate that our proposed model reduces computational complexity by 0.6 GFLOPs and decreases parameters by 279604 compared to the base YOLOv8 model. This leads to a minor accuracy improvement of 0.0117. (*Abstract*)**

***Keywords*— Object Detection, Multiple object tracking, Deep learning, Computer vision**

I. Introduction

Since children's immune and digestive systems are not as developed as adults, it is essential to check whether children's snacks contain foreign matters and harmful matters during the manufacturing process.

The existing methods for identifying foreign matters and defects in children's snacks mainly use manual inspection and computer vision technology that does not include deep learning technology. However, manual inspection has the disadvantage of not guaranteeing a constant yield depending on the worker's ability and condition and taking a long time. To overcome the problems of manual inspection, some manufacturers use computer vision systems that apply rule-based algorithms. However, rule-based algorithms have difficulty handling real-world foreign matters with various shapes, textures, and colors.

Object detection technology that identifies foreign matters has also been greatly improved by utilizing deep learning in various fields, and a representative example is YOLO (You Only Look Once) [1]. Using YOLO, foreign matters can be detected before packaging during the manufacturing process to ensure the safety of children's snacks. However, in order to utilize the YOLO model for foreign matter detection that requires high accuracy, many parameters and high computational costs are required. Due to these requirements, it is known that deploying YOLO in resource-constrained environments or low-power devices is limited.

In this paper, we propose an approach that reduces the number of parameters and computational load of the YOLOv8 model by integrating the Ghost module [2] and the Efficient Channel Attention (ECA) module [3] while improving the accuracy of detecting defects and foreign matters in children's snacks.

II. Method

The structure of YOLOv8 is an algorithm that inherits the advantages of the existing YOLO model, but applies the latest object detection technology, such as using an anchor-free model that directly predicts the center of the object instead of the kernel box. In particular, the backbone network of YOLOv8 plays an important role in feature extraction, and various information of the input image is extracted through this backbone part.

The proposed YOLOv8 model is composed of the backbone network, neck, and head. In this structure, instead of using the existing convolution block [4] for the backbone, we replaced the convolution block of the backbone with the Ghost module. The Ghost module can extract features of a similar level with a small amount of computation, greatly improving the computational efficiency of YOLOv8. In addition, the ECA module is located in the neck to further highlight important channel features. The neck part integrates features and organizes them into a form that can ultimately detect objects, and by applying the ECA module, important information for detection can be efficiently transmitted.

The Ghost module is a feature extraction block that can maintain sufficient expressiveness with a small number of parameters and computations. The existing convolution block requires large computations, but the Ghost module achieves a similar effect by making it lightweight. The Ghost module first generates a main feature map through a convolution operation, and then generates additional feature maps through low-cost computations based on it to obtain the final feature map. This method can reduce the computational amount of the entire model while maintaining performance, so by replacing the convolution block in the backbone network of YOLOv8 with the Ghost module, the model can be made lightweight and faster at the same time.

The ECA module is located at the neck of YOLOv8 and helps focus more on important features by efficiently considering the relationship between channels. In general, the

Bulletin of Networking, Computing, Systems, and Software – www.bncss.org, ISSN 2186-5140
Volume 14, Number 1, pages 34–35, January 2025

Attention module helps the network focus on important features. In particular, the ECA module captures channel-by-channel interactions with a very small computational amount and operates more efficiently. While the existing channel Attention module requires a significant amount of computation, ECA learns channel relationships through 1D convolution, so it has a faster and lighter structure. This allows the detection performance to be improved without significantly increasing the computational cost of the model.

III. Experiments and Results

The system configuration for obtaining the dataset consists of lighting, a dark room, and a conveyor belt, including machine vision, as shown in Figure 1. The classification categories of the dataset are divided into normal children's snacks, damaged children's snacks, and foreign matters, and a total of 11133 self-datasets were collected. At this time, foreign matters consist of objects that should not be included with children's snacks, such as paper and plastic. The version of YOLOv8 used in the experiment was the nano version model, which is the smallest among various official versions.

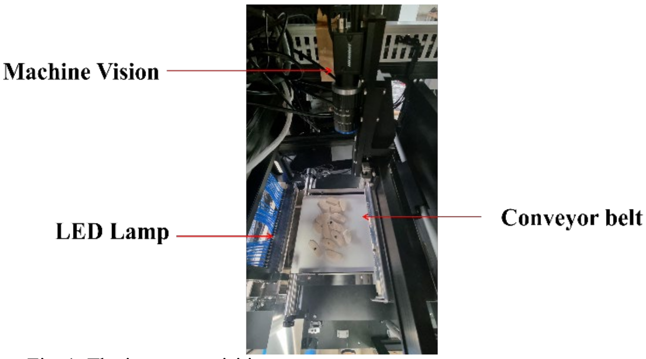

Fig. 1. The image acquisition system.

In the experiment, the base model had 3011417 parameters, 8.2 GFLOPs, and 0. 7572 accuracy. When the convolution block was changed to the Ghost module, the number of parameters decreased to 2731411 and the computational complexity decreased to 7.6 GFLOPs, but the accuracy slightly decreased to 0.7524. On the other hand, when the ECA module was added to the Ghost module, the number of parameters slightly increased to 2731813, but the computational complexity remained the same at 7.6 GFLOPs and the accuracy improved to 0.7689. As a result, the proposed method reduced the computational complexity by 0.6 GFLOPs and the number of parameters by 279604 compared to the YOLOv8 base model, and improved the performance by 0.0117. As illustrated in Figure 2, the detection results for foreign matters using the proposed method demonstrate its effectiveness in identifying contaminants within children's snacks.

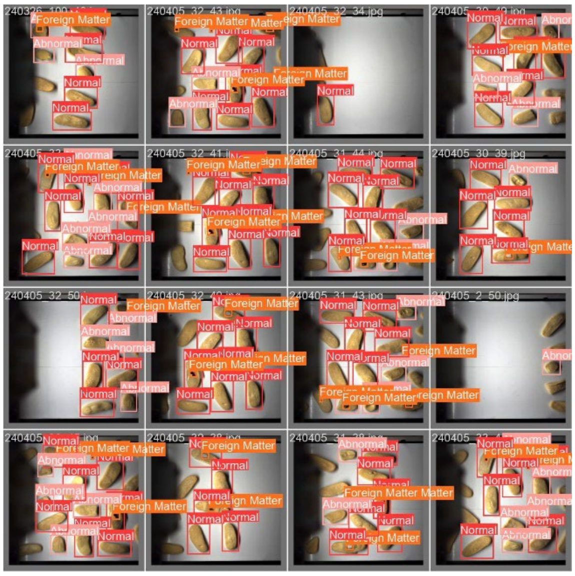

Fig. 2. Foreign matters detection results using the proposed method.

IV. Conclusions

In this study, we applied the Ghost module to the backbone network of the YOLOv8 model to reduce the computational cost, and added the ECA module to compensate for the accuracy decrease that may occur due to the reduced computational cost. Through this, we achieved performance improvement by reducing the computational complexity by 0.6 GFLOPs and the number of parameters by 279604 compared to the basic YOLOv8 model, while increasing the accuracy by 0.0117. The model proposed in this study proved that it can show high efficiency and accuracy in detecting defects and foreign matters in children's snacks, especially in resource-constrained environments.

Acknowledgment

This work is supported by a grant (no. 22193MFDS466) from MFDS of Korea And, this work was also supported by DGIST research project (24-IT-01).

References

[1] JIANG, Peiyuan, et al. “A Review of Yolo algorithm developments.” Procedia computer science, 2022, 199: 1066-1073.

[2] HAN, Kai, et al. “Ghostnet: More features from cheap operations.” In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2020. p. 1580-1589.

[3] WANG, Qilong, et al. “ECA-Net: Efficient channel attention for deep convolutional neural networks.” In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2020. p. 11534-11542.

[4] LECUN, Yann, et al. Backpropagation applied to handwritten zip code recognition. Neural computation, 1989, 1.4: 541-5