Glass Wool Defect Detection Using an Improved YOLOv5

Yizhou Jin, Yu Lu, Gang Zhou, Qingjie Liu, Yunhong Wang
{yizhou.jin, qingjie.liu, yhwang}@buaa.edu.cn, {luyu, zhougang}@bhhzcxyjy.wecom.work

Problem

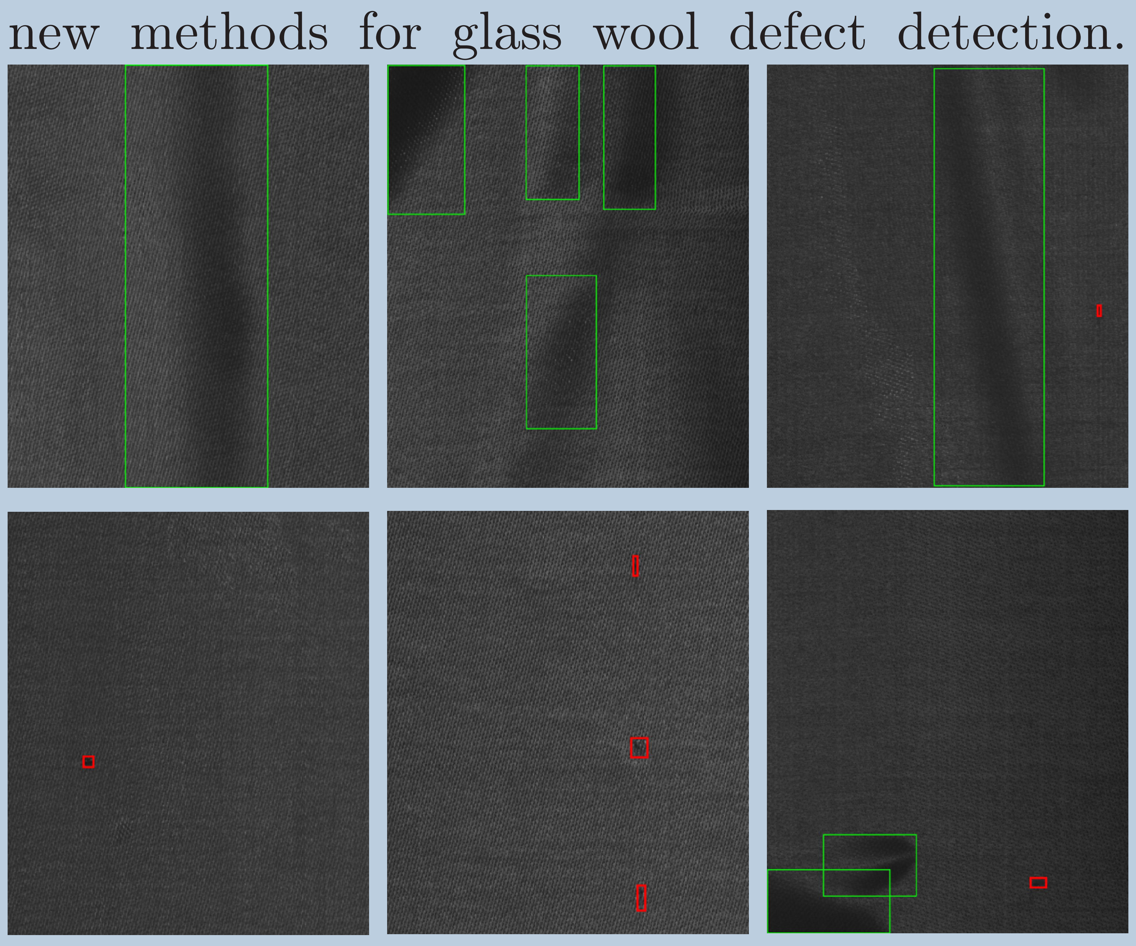
Glass wool is widely used as insulation material, and its quality directly affects the energy efficiency and safety of buildings. However, due to the complex manufacturing process and the variability of defects, it is difficult to accurately detect and classify glass wool defects using traditional methods. Therefore, this work proposes a novel method based on YOLOv5 algorithm with GSConv and CBAM modules to improve detection accuracy and provide a new solution for glass wool defect detection.

Contributions

(i) we constructed a glass wool defect detection dataset named GWD, which to the best of our knowledge is the first dataset on glass wool defects.
(ii) we investigated the performance of YOLOv5n, YOLOv5s, and YOLOv5m models on the proposed dataset, respectively, and discovered that these models struggled to detect defects in glass wool and pinpointed the primary problems.
(iii) an improved YOLOv5 model applicable to glass wool defect detection is proposed, which achieves 84.1% mAP50 and 84.4% recall on the GWD dataset, with inference speed up to 97 FPS measured under RTX 2080Ti GPU.

GWD dataset

The GWD dataset proposed in this work is the first glass wool defect dataset and contains 1,000 images of 10 defect categories. It was collected in a factory and annotated with bounding boxes. The dataset provides a valuable resource for developing and evaluating new methods for glass wool defect detection.

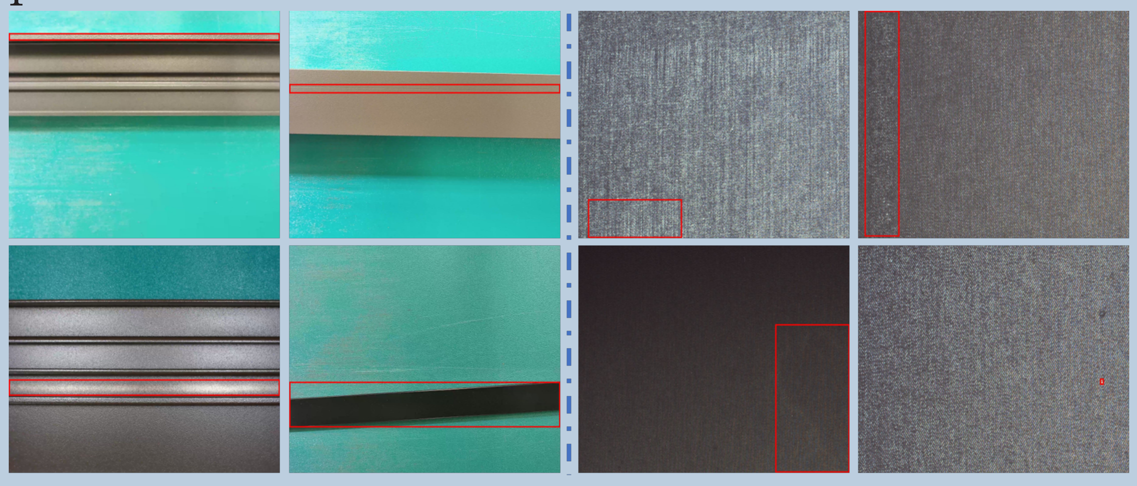


(a) (b) (c)

The GWD dataset can be obtained by contacting us via email.

Other public datasets

In addition to the Glass wool defect dataset, we evaluated our proposed model on two additional datasets.



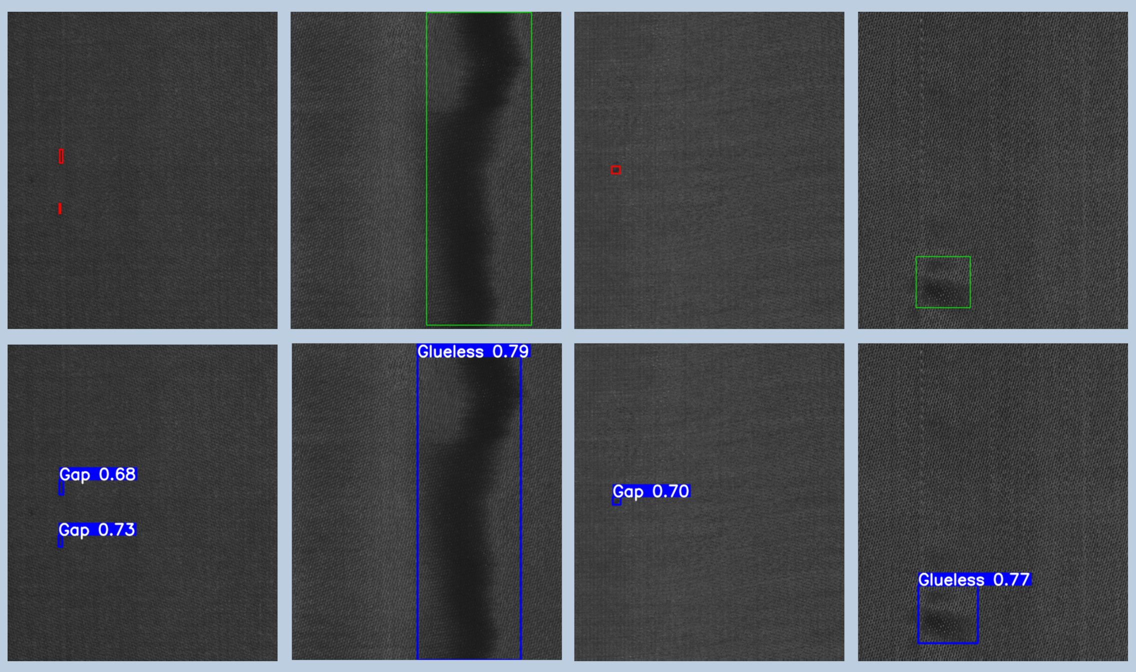
(a) ADD Dataset (b) FDD Dataset

We evaluated our proposed model on two benchmark datasets: the Aluminum Defect Dataset (ADD dataset) and the Fabric Defect Dataset (FDD dataset). The ADD dataset consists of 3,004 images with 10 defect categories, while the FDD dataset contains 3,000 images with 6 defect categories from diverse sources. These datasets allowed us to assess our model's performance on different types of defects and materials and compare it with state-of-the-art methods.

Results on GWD dataset

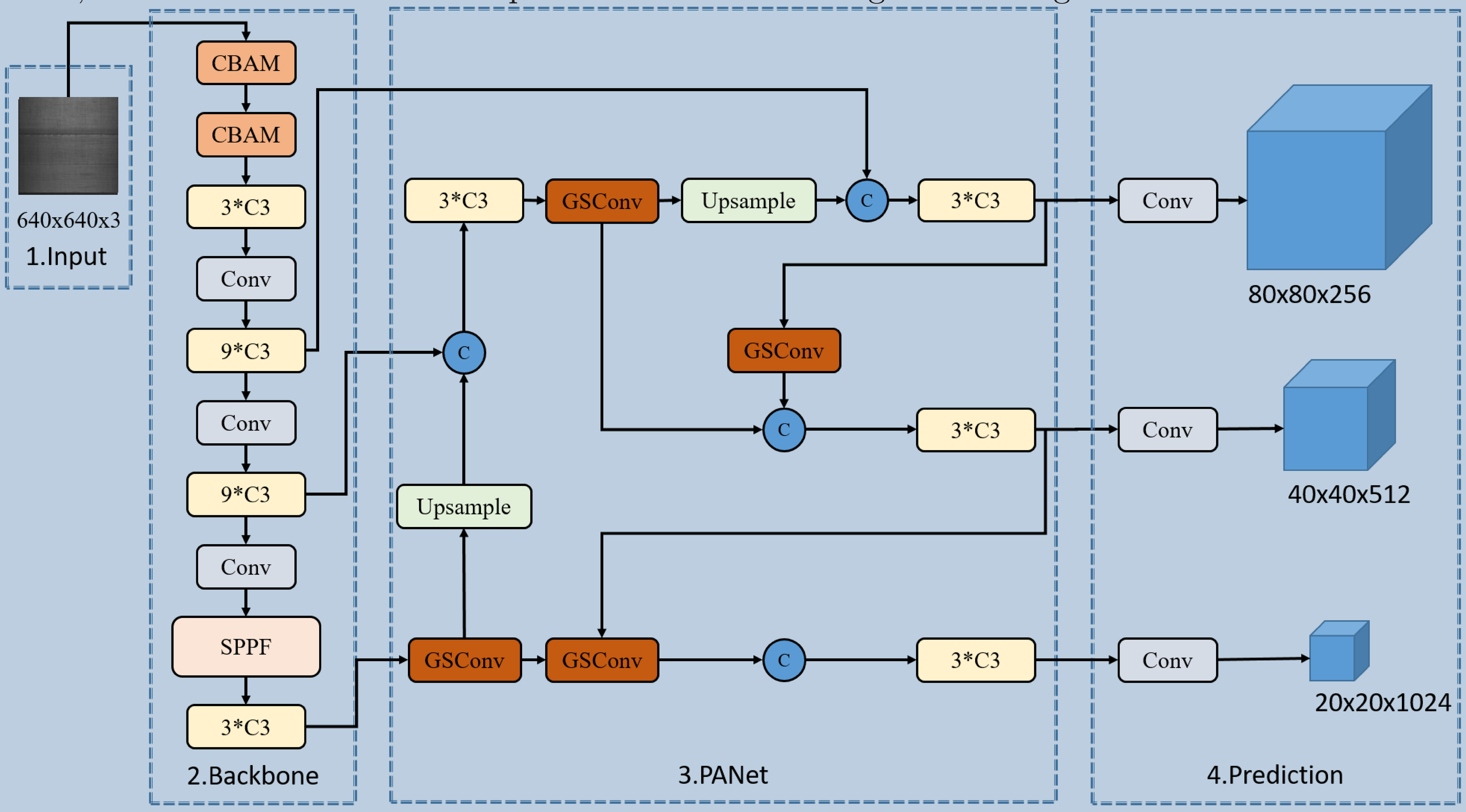
We perform ablation studies based on YOLOv5n, YOLOv5s and YOLOv5m:

Model	CBAM	GSConv	mAP50(%)	Params(MB)
YOLOv5n			81.1	**1.68**
	✓		82.3	1.69
		✓	**82.7**	1.58
	✓	✓	**83.1**	**1.58**
YOLOv5s			80.4	6.69
	✓		81.4	6.70
		✓	**83.7**	**6.30**
	✓	✓	**84.1**	**6.27**
YOLOv5m			81.5	**19.91**
	✓		**82.1**	19.91
		✓	81.6	18.96
	✓	✓	**83.9**	**18.96**



Improved YOLOV5

The proposed glass wool defect detection model is based on the YOLOv5 algorithm and optimized with modifications including the CSPDarknet backbone network, PANet module for feature fusion, and Output module for object detection. Two novel modules, GSConv and CBAM, are introduced to further optimize the YOLOv5 algorithm for glass wool defect detection.



These modules were added to improve the model's performance on glass wool defect detection, with GSConv reducing computation costs while maintaining accuracy, and CBAM enhancing feature representation for small defects in complex backgrounds.

Comparison with other methods

A series of comparative experiments are conducted on the proposed GWD and other datasets to compare the proposed model with various other models.

Algorithm	Backbone	mAP50(%) GWD dataset	mAP50(%) ADD dataset	mAP50(%) FDD dataset	Param(MB)	Flops(GFLOPs)
Cascade R-CNN	Resnet50	**82.0**	**74.0**	**64.4**	68.88	116.91
Faster R-CNN	Resnet50	77.2	69.6	63.4	33.57	775.61
SSD	VGG16	80.3	70.8	61.2	36.04	154.4
SSDlite	Mobilenetv2	72.1	67.7	55.8	**4.23**	**3.15**
YOLOv7	CSPDarknet	75.7	72.1	58.4	36.49	105.1
YOLOXs	CSPDarknet	78.4	71.3	62.5	8.94	13.32
YOLOv5s	CSPDarknet	80.4	73.8	63.5	6.69	16
Ours	CSPDarknet	**84.1**	**74.9**	**65.3**	**6.27**	**15.4**

As shown in Tab, our proposed method achieved the best performance on all three datasets, even with a smaller model size and faster inference speed. This indicates that our method is effective in various materials and can be applied to real-world scenarios with limited computing resources.

References

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[2] Wang et al. *ECA-Net: Efficient channel attention for deep convolutional neural networks.* Proceedings of the IEEE/CVF CVPR (2020)

Acknowledgements

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