An Automatic Bridge Cable Surface Inspection System Based on Machine Vision and Deep Few-Shot Learning*

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***Abstract*— There is a growing demand for automatic bridge inspection using intelligent detection technologies to replace manual inspection. This paper proposes an automatic bridge cable surface inspection system based on machine vision and deep few-shot learning technologies. The proposed system is able to acquiring high-quality images on bridge cables using high-resolution cameras and artificial lighting, and can be easily integrated with our bridge cable climbing robots. A deep-learning based few-shot object detection algorithm is adopted to perform cable damage detection. Cross domain knowledge transfer is exploit so that the deep learning model can learn to identify cable damage by given a few samples. To train and evaluate the proposed deep learning model, a few-shot bridge cable damage detection dataset is made. Experimental results show that our method can adapt fast to detect 3 type of typical cable damages (crack, dirt and patch damages). To the best of our knowledge, this is the first deep few-shot learning based method for bridge cable defect detection.**

I. Introduction

Cables are the main load-bearing members of cable stayed bridges. The damages on the Polyethylene envelopes of bridge cables cause corrosion inside cables and significantly shorten the service life. Thus, they need periodic inspection and maintenance during use. Manual cable inspection by inspectors is costly, time-consuming and risky. Autonomous inspection using robots is a promising way to tackle those problems. Although, many robotic platforms have been developed for bridge cable inspection that can climb along the cables to acquire data for diagnosing [1], the acquired data is still inspected manually. In addition, the number of literatures that report automatic cable damage detection methods is much smaller than that of literatures reporting robot platforms. Existing problems of automatic cable surface inspection research include:

1) Insufficient research. Most existing methods use traditional machine learning methods without validation in real circumstance. Although, deep learning has been widely used in other visual detection tasks and surpasses traditional methods with large margins, we can hardly find deep-learning based cable damage detection methods in literatures.

2) Lack of datasets. There are a variety of damages that can be found on bridge cables, and the appearance of damages on different bridges varies from case to case. The damage images are hard to obtain, and labeling those data needs professional operators and the procedure is time-consuming. Currently, there is no large scale open-source dataset for training and evaluating a cable damage detection method. This may be the reason why there is a lack of deep learning application within this research community.

3) Unsatisfactory quality of acquired images. For the ease of data transmission and to simplify the structural design, most existing machine vision systems for bridge cable inspection uses IP cameras and uncontrolled lighting condition, as shown in Fig. 1(a). The quality of acquired images is unsatisfactory for subtle damage inspection. The changing intensity, complex background and partial shadow in the images bring difficulty in image processing.

This work seeks to fill those gaps in fulfilling accurate automatic bridge cable surface inspection. The main contribution of this paper can be summarized as follows:

1) A machine vision system is built for bridge cable inspection, which can acquire high-quality images using high-resolution cameras and artificial lighting, and transmit the images to the ground control station wirelessly in real-time. It

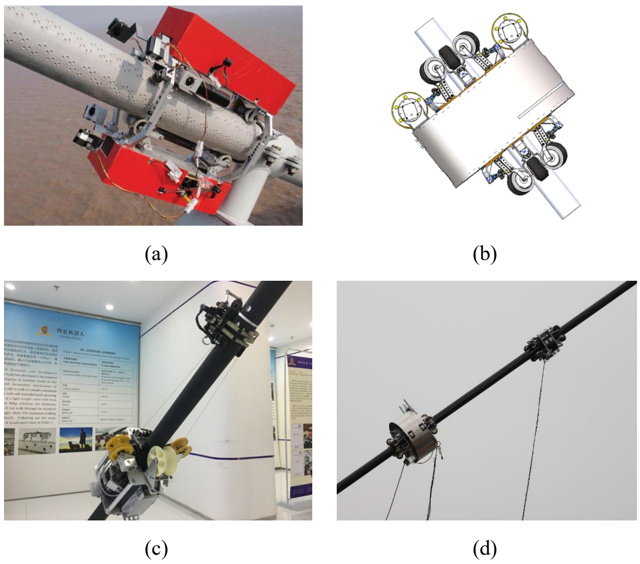

Fig. 1 Comparison of the proposed cable inspection system with a traditional solution. (a) A typical cable inspection robot with four cameras acquiring images under natural illumination [2]. (b) Our cable inspection system is designed with a full-covered structure to ensure a stable imaging condition. (c) Our previously proposed cable climbing robot CCRobot-III [3]. (d) Our cable inspection system can be easily integrated with a climbing precursor similar to that of our CCRobot-III.

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can be easily integrated to our bridge climbing robots [3] [4], as shown in Fig. 1(d).

2) A deep few-shot learning based cable damage detection method is adopted, which can be trained with only a few samples. A few-shot cable damage detection dataset is built to train and evaluate the detection model following typical few-shot learning protocol. To the best of our knowledge, this is the first deep few-shot learning solution for bridge cable surface inspection.

II. Related Work

There is growing interest in developing bridge cable inspection robots. Most of the robots have equipped with digital cameras to record videos or take pictures on the cable surface to replace manual data collection. Typical examples are the robots reported in [2], [5], [6]. However, the procedure of finding the cable damages within the collected data still relies on human inspectors. The cameras equipped on the robots are usually exposed to the daylight, which result in the changing illumination, partial shadow, and complex background in the images.

A few literatures have reported automatic bridge cable surface damage detection methods. Ho *et al*. [7] propose a cable damage detection system installed on a cable inspection robot. The system has 3 cameras embed on a closed box lighted by light emitting diodes (LEDs) to maintain a stable illumination. They propose a cable damage detection algorithm that combines image enhancement techniques with the principal component analysis (PCA) algorithm and a Mahalanobis square distance classifier. Li *et al*. [8] propose a machine vision system for a bridge cable inspection robot. The system contains 4 CCD cameras, and detect damages by means of Sobel edge detection and morphological operations. Furthermore, the scale-invariant feature transform (SIFT) algorithm is used to achieve the multi-image mosaic with partially overlapped regions in different defect images. Later, Li *et al*. [9] propose a cable damage recognition method that extracts 10 kinds of features including shape, texture and gray scale and inputs the features to a Support Vector Machine classifier optimized by the Particle Swarm Optimization algorithm. So far, most of the existing bridge cable damage detection methods are based on digital image processing techniques, feature engineering and traditional machine learning. But in real-world scenarios, the acquired cable images usually contain complex background and unstable illumination with a large variety of damage appearance, traditional methods can hardly achieve robust performance.

Very recently, some researchers apply deep learning on this domain. Yu [10] adopts Faster R-CNN to detect bridge cable damage, and achieved a significant improvement on accuracy over traditional methods. The Faster R-CNN model is trained with over 800 images of 6 types of cable surface damages. Hou *et al*. [11] propose a Cascade Mask R-CNN based method for cable damage segmentation. They exploit transfer learning from concrete crack images to reduce the data needed for training the deep learning model. However, they still use more than 5600 cable damage images to train the model.

According to our literature survey, the application of deep learning on cable damage identification has just been started and very few literatures can be found. The reason causing the lack of deep learning based solutions is probably the data-hungry characteristic of deep learning models, as large-scale bridge cable damage dataset is extremely hard to obtain.

In order to learn from a limited number of examples with supervised information, a machine learning paradigm called Few-Shot Learning (FSL) [12] is attracting more and more attention in machine learning research community. FSL can help to relieve the burden of collecting large-scale supervised data, and promote the application of deep learning in a variety of tasks that lacks large-scale data. The audience can refer to [13] for a recent literature review on FSL.

In this work, we try to tackle the cable damage detection problem in a few-shot learning way. We propose a deep-learning based few-shot object detection algorithm to perform cable damage detection. Cross domain knowledge transfer is exploit so that the deep learning model can learn to identify cable damage by given a few samples. To the best of our knowledge, this is the first deep few-shot learning based method for bridge cable defect detection

III. Proposed Method

In this section, the structure and components of the cable inspection vision system will be introduced, followed by the detailed description of our few-shot cable damage detection dataset and method.

A. Cable Inspection System

We design a cable inspection system (depicted in Fig. 2) that can move along the bridge cables and carry a machine vision system to collect high-quality images of the bridge cable surface. The system can be easily integrated with a climbing precursor similar to that used in our CCRobot-III, as shown in Fig. 1(d). They are connected through steel wires and cooperate in such a way that the lightweight precursor moves rapidly to the top of the cable and fastens itself to the cable using gripping palms (the design and working principle of the gripping palms is described in [3]), then the cable inspection system lifts itself by rolling up the steel wires using two winches. The wheels and clamping mechanisms guide the cable inspection system the move along the bridge cable. The system is able to move smoothly on regular cables, dimpled cables, and cables with spiral wires at a maximum speed of 0.2 m/s.

The machine vision system equipped in the proposed cable inspection system consists of 4 high resolution industrial

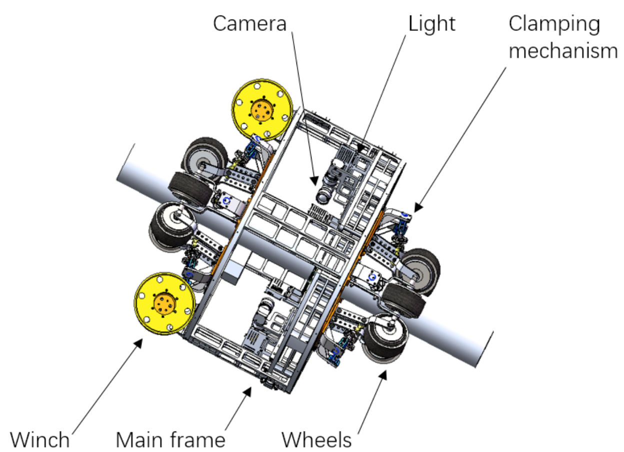


Fig.2 The structural design of the cable inspection system.

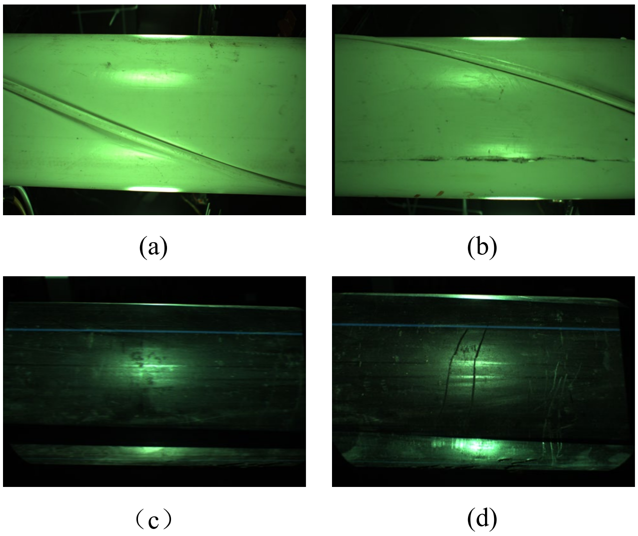


Fig.3 Examples of cable surface images acquired by our cable inspection system. (a)and (c) are cable surface images without damage. (b) and (d) are cable surface images with a crack and scratch, respectively.

cameras (DO3THINK M3ST507-H), 4 LED lights and a micro personal computer (Intel NUC 8). The industrial cameras are uniformly distributed, so that the field of view of the 4 cameras covers the surface of the cable circumferentially. Each of the camera has a maximum resolution of 2248×2048 and can reach submillimeter precision. To create a stable lighting condition, the cable inspection system is covered with a metal sheet to block out the daylight, and 4 LED lights are used of illumination. As a result, our system guarantees the high quality of the acquired images which is beneficial for image process and damage analysis. The acquired images are transmitted to the ground console wirelessly in real time for on-line monitoring. As the size of the raw images output from the cameras is too large for real-time wireless transmission, they are compressed in advance. The full resolution raw images are saved to the hard disk of the micro personal computer for off-line processing. A few examples of the acquired images are shown in Fig. 3.

B. *Deep Few-Shot Cable Damage Detection Model*

Traditional deep learning methods requires large amounts of annotated data to train the models. However, bridge cable damage occurs infrequently, and obtaining and annotating the damage samples are costly. This contradiction hinders the application of deep learning technology on cable damage detection.

Seeking to fill this gap, we propose a deep few-shot leaning method for cable damage detection. We adopt the few-shot object detection method with attention-RPN and multi-relation detector proposed by Fan *et al*. [14], and exploit cross-domain knowledge transfer from general object detection tasks and industrial defect detection tasks to the cable damage detection task. The adopted few-shot learning model [14] is based on the Faster R-CNN [15] framework while the novel attention region proposal network (RPN), multi-relation detector, and contrastive training strategy are introduced, as shown in Fig.4. The model learns a general matching relationship between the support set and queries on both the attention-based region proposal network and the multi-relation detector. Specifically, the attention RPN computes depth-wise cross correlation between the support feature and the query feature, and use it as attention features to enable filtering out most region proposals belong to the background and non-matching categories. At the end of the model, the detector in original Faster R-CNN framework is replaced with a multi-relation detector to effectively measure the similarity between the generated region proposals of the query image and the support samples. The multi-relation detector includes 3 attention modules, i.e., the global-relation head, the local-correlation head, and the patch-relation head. The detailed structure can be referred to [14]. Furthermore, a novel 2-way contrastive training strategy is applied for distinguishing different categories and matching the same ones. The model has achieved state-of-the-art performance on several benchmark object detection datasets in terms of 5-shot and 10-shot object detection. Another important characteristic of the model is that it can achieve relatively high accuracy for detecting objects of novel categories without retraining or fine-tuning after trained on the 1000-categry FSOD dataset [14] (retraining and fine-tuning can bring better accuracy).

C. *Cross-Domain Knowledge Transfer*

Although, the few-shot object detection method with attention-RPN and multi-relation detector used in this work can be used directly without fine-tune after trained with the FSOD dataset [14], the scenarios included in the FSOD dataset is quite different from our specific cable damage detection scenario.

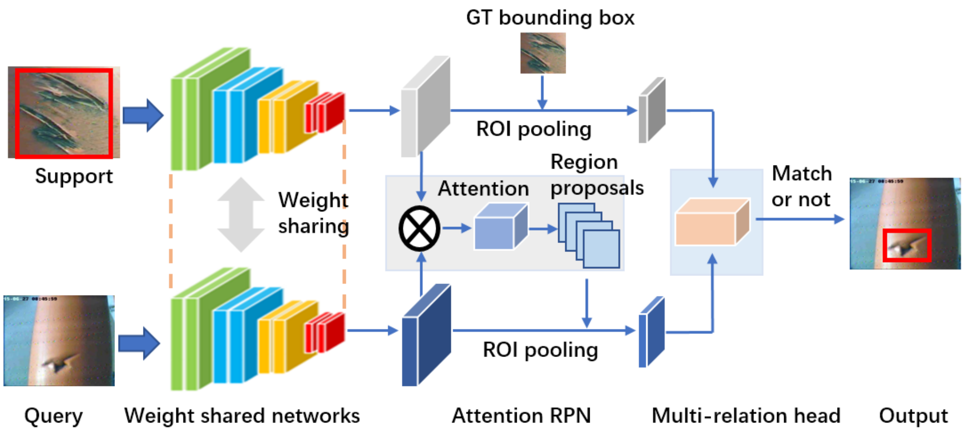
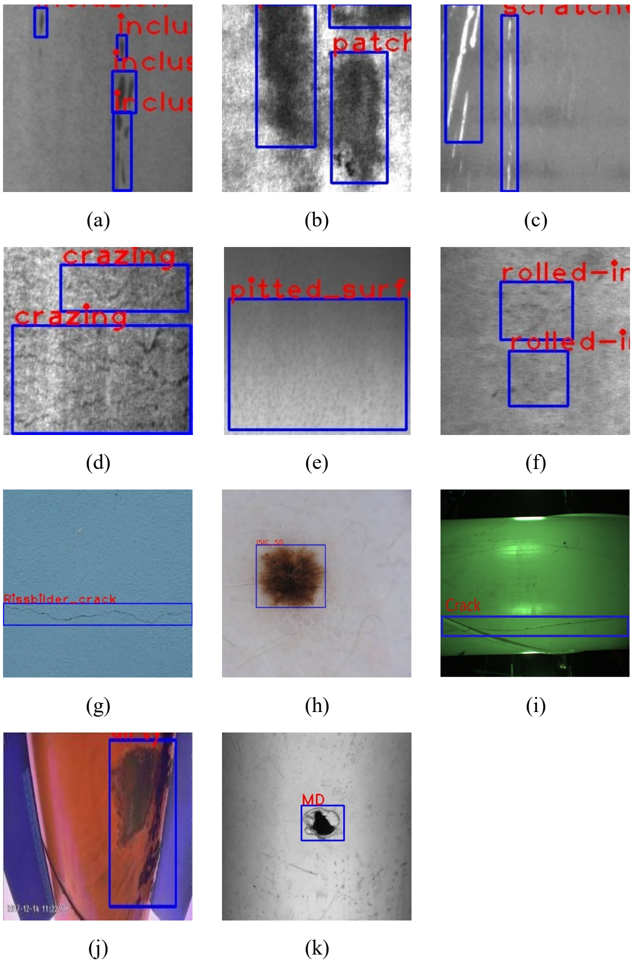


Fig. 4 Illumination of the deep few-shot cable damage detection network framework. For a detailed illustration of the attention RPN and multi-relation head, the audience can refer to [14].



(a) (b) (c) (d) (e) (f) (g) (h) (i) (j) (k)

Fig.5 Some examples in our dataset. (a) to (f) are hot-rolled steel strip defects selected from NEU-DET dataset [17], they are inclusion, patches, scratches, crazing, pitted surface, roll-in scale. (g) is civil structure crack selected from [18]. (h) is pigmented skin lesion selected from HAM10000 dataset [19]. (i) to (k) are cable crack, cable dirt and cable patch damage, respectively.

What's more, there is no publicly available dataset for bridge cable damage detection so far, and it is hard to obtain cable damage samples even using a robotic inspection platform due to the infrequent occurrence of damages. To improve the accuracy of the cable damage detection model, our thought is to make use of existing datasets that are out of the cable damage domain but have some similar properties, to pretrain the model and fine-tine the model with a few samples of cable damages.

We made a dataset to pretrain, fine-tune and test the cable damage detection model. Following the common few-shot learning paradigm [14], [16], our dataset contains base class images for pre-training the detection model, and novel class images for fine-tuning and testing the model. The base classes images are selected from existing open-source datasets other than bridge cable damages. In this research, we select images of 8 categories, including 6 types of industrial product defects from the Northeastern University surface defect database (NEU-DET) [17], civil structure crack images from the dataset made by Liu *et al*. [18], and images of pigmented skin lesions from the HAM10000 dataset [19]. Each category contains 300 images, except for the skin lesion category (which contains 292 images). We annotate the target region with bounding boxes following the PASCAL VOC format [20]. We take 50 images in each category for validation, and the others are used for training. For the novel class, we collected 3 types of typical bridge cable damage, including crack, dirt and patch damage (actually includes pothole and surface corrosion), with 34, 29 and 29 images, respectively. Those damage samples are either collected with our cable inspection system or previously collected using other equipment. In each category, 10 images are left out as support set. Some examples in this dataset are shown in Fig. 5.

IV. Experiments

In the experiments, we firstly test the motion capacity and image acquisition function of the proposed cable inspection system. Secondly, we evaluate the accuracy of the proposed deep few-shot cable damage detection method by conducting few-shot damage detection test and fair comparison with another state-of-the-art few-shot object detection methods proposed in [16].

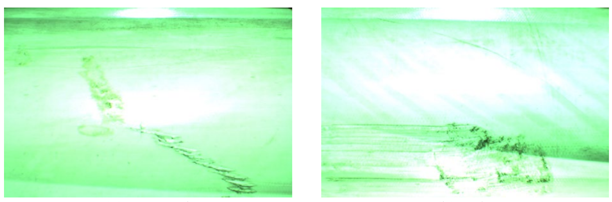
A. Experimental Setup

To validate the motion capacity and image acquisition function of the proposed system, we test our system on real bridge cables at the bridge cable test field of Chongqing Wanqiao Communication Tech Co. Ltd. and a long-span cable stayed bridge in Chongqing. A total of 352 images and 256 images are acquired at the test field and real bridge, respectively, and a few damage samples are obtained, as shown in Fig. 6. The cable inspection system moves smoothly upward and downward along the cables, and the acquisition, data transmission and saving procedures are all conducted successfully. The audience can refer to our video to see how the system works on site.

We test the adopted deep few-shot learning method and compare it with another few-shot object proposed in [16] in 4 common few-shot learning experiment setup including 3-way-5-shot and 3-way-10 shot. (For the ease of notation, we call the method in [16] FR for short, and call the adopted method [14] FAM for short.) We also try to take away 3 base classes (crazing, pitted surface, and rolled-in scale) to see the effect of the number of reducing classes in the base set. The Average precision (AP), which are commonly used metrics for object detection are used to evaluate the detection accuracy of the proposed method. Specifically, AP is measured with AP_{25}, and AP_{50}.

B. Implementation Details

The proposed method is implemented with PyTorch developed by FaceBook. The CNN model is trained with 4 NVIDIA Titan Xp GPUs. Hyper parameter used in model training and fine-tuning include: batch size (128), initial learning rate (0.002), training steps (60,000 for pretraining and 100 for fine-tuning), and optimizer (SGD).



(a) Scratch (b) Dirt

Fig. 6 Obtained cable damage samples

TABLE I. RESULTS (AP_{25}) OF FEW-SHOT DAMAGE DETECTION

Method	Base class	Fine-tune strategy	Crack	Dirt	Patch damage
FAM	8 class	3w5s	0.382	0.331	0.462
		3w10s	0.424	0.304	0.511
	5 class	3w5s	0.360	0.167	0.359
		3w10s	0.397	0.200	0.345
FR	8 class	3w5s	0.091	0.0	0.205
		3w10s	0.227	0.136	0.503
	5 class	3w5s	0.273	0.182	0.182
		3w10s	0.460	0.255	0.367

The *nwks* denotes *n*-way-*k*-shot setting.

TABLE II. RESULTS (AP_{50}) OF FEW-SHOT DAMAGE DETECTION

Method	Base class	Fine-tune strategy	Crack	Dirt	Patch damage
FAM	8 class	3w5s	0.315	0.257	0.447
		3w10s	0.326	0.247	0.497
	5 class	3w5s	0.153	0.095	0.349
		3w10s	0.131	0.156	0.341
FR	8 class	3w5s	0.091	0.0	0.091
		3w10s	0.227	0.0	0.441
	5 class	3w5s	0.182	0.0	0.182
		3w10s	0.339	0.182	0.266

FR is also implemented with PyTorch. For the training of FR, either NVIDIA RTX 2080 TI or Titan Xp GPUs are use. The hyper parameters in training and fine-tuning includes: batch size (64), learning rate at both training and fine-tuning (0.001), learning rate burn-in steps (1000), training steps (10000 for pretraining and 500 epochs for fine-tuning), and optimizer (SGD).

V. RESULTS AND DISCUSSION

The quantitative test results of the our deep few-shot cable damage detection method and the compared method are listed in Table I, and Table II.

As can be seen from the results, FAM significantly outperforms FR in all the scores, which shows the superiority of FAM on few-shot learning ability. For both of the methods, they perform worst on dirt.

To FAM, sometimes, the accuracy of 10-shot is worse than that of 5-shot, while for FR, the accuracy of 10-shot is always much better than that of 5-shot. This indicates that, for FAM, the pretraining procedure is more important than the fine-tuning procedure, while it is on the opposite side for FR.

When reducing the number of classes in the base set, the two methods behave differently. The accuracy of FAM drops when using less base classes, while the accuracy of FR benefits from the reduction of less base classes. This indicates the difference in the way that the two methods learn to recognize the features in different categories. As the number of output classes increases when more base classes or novel classes are added, the model has to predict more object categories. For FAM, the number of base classes does not affect the number of prediction categories. To this end, we think the FAM is a more flexible method.

VI. CONCLUSION

This paper proposes an automatic bridge cable inspection system based on machine vision and deep few-shot learning technologies. A machine vision system is designed for acquiring high-quality images of cable surface, and a deep few-show learning based cable damage detection method is proposed by adopting few-shot object detection techniques and cross-domain knowledge transfer. The proposed cable inspection system can be integrated well with our previously proposed robot and efficiently acquire high-resolution image on real bridge cables. The deep few-shot learning based cable damage detection method can be trained with base dataset from out of the target task and fine-tined with a few target samples to reach a relatively good accuracy. The experimental result shows that our method is a superior and effective solution in few-shot cable damage detection.

Future work can be done on the lightweight design of the proposed system and the further integration of the proposed system with our bridge climbing robots. The dataset will be extended by adding both more base classes and cable damage samples. Also, the defect detection algorithm should be improved for on-board real-time inferencing.

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