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Integrating Object Detection and Deep Learning for Oil Painting Paint Layer Defect Detection

[1] Yu-Ting Wu, [2] Chwen-Tzeng Su, [3] I-Cheng Li, [4] Shou-Che Wu

[1] [2] National Yunlin University of Science and Technology, Douliu, Taiwan.
[3] [4] Cheng Shiu University, Kaohsiung, Taiwan.
Corresponding Author Email: [1] m11021009@yuntech.edu.tw, [2] suct@yuntech.edu.tw, [3] plastic@gcloud.csu.edu.tw, [4] k0348@gcloud.csu.edu.tw

Abstract— ***The application of machine learning, deep learning, object detection and other related technologies has gradually matured, but in the field of cultural asset protection and art restoration, related applications are just about to begin. In the process of reviewing the restoration status of the works, in the past, it was necessary for the restorer to manually mark the missing position, which resulted in a lot of time and energy consumption, and sometimes there was a possibility of misjudgment due to the restorer's experience. To solve those problems, this study intends to use object detection technology to assist restorers to speed up the efficiency of missing annotations in the work inspection process.***

This study proposes to use YOLOv5 object detection technology to detect defects in the painted layer of oil paintings, assist restorers to save time in manually marking damaged areas, and devote more time and energy to painting restoration operations. This study uses two non-destructive examination techniques, Ultraviolet and Normal light, to identify retouching, insect excrement, and painted layers loss. hoped this will give some technical assistance to the field of art restoration. Some repair techniques are combined with today's computer technology to improve the effect of repair and reduce the consumption of manpower and time.

Index Terms—Art Restoration, Defect Detection, Oil Painting Paint Layer Defect, YOLOv5.

I. INTRODUCTION

With the rapid advancement of technology, the application of machine learning, deep learning, AI, object detection and other related technologies have gradually matured, and with the evolution of time, the cost of entering the technology field has also been reduced. In addition to many successful cases and applications in the industrial and medical fields, related technologies are also beginning to be widely applied in people's daily lives. At present, the restoration field is facing three major problems: firstly, there is a general shortage of professionals in the restoration field; secondly, there is a gap between old and new restorers in terms of skills and experience transmission; and thirdly, a lot of precious time is spent on preoperative inspection and post-marking deficiencies, and these problems seem to have some new solutions as time and related technologies mature. The most common applications of machine learning and deep learning in the field of restoration or art industry can be broadly classified as artist identification, forgery detection, crack detection, defect detection of paintings or works, and virtual restoration [1].

In terms of defect detection, depending on the material of the work, there are six major categories of defects: Support, Paint layers, Protect layers, Stretcher, Frame, and Pedestal. The AI-aided drawing is used to repair defect detection operations, and many applications still focus on cracks as the research direction, while other types of defects such as Retouching, Mold, Loss, Dent, etc. have less research and application. Therefore, the main direction of this study will focus on the defects of oil painting layer as the main axis, through the application of object detection technology, compared to the traditional way of manually marking defects, so that the restorer can improve a certain degree of efficiency in the restoration inspection operation.

The purpose of this study is to optimize the condition inspection process in the restoration field through the application of object detection YOLO (You Only Look Once) technology. It is also intended to detect defects in the artwork to be restored. The use of technology effectively reduces the restorer's operating time in the inspection process and assists in the process of defect marking and condition type description. We hope that this theme will provide some new technical assistance in the field of art restoration, combining the existing restoration techniques with the current computer technology to improve the effectiveness of restoration, reduce the time cost of defect detection, and reduce the consumption of restoration labor. The repair flowchart is given in Figure1.

Figure 1. Repair flow chart

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II. RELATED WORK

Scholars [2] who applied the YOLOv3 object detection method to detect cracks and defects in wooden architectural heritage, showed that the method took less than 0.1 seconds per image and achieved an accuracy rate of more than 90%, demonstrating that the use of deep learning object detection techniques is more accurate, faster, and more robust than traditional manual detection methods. It also proves that using YOLOv3 object detection method is effective and reliable. Scholars [3] proposed the use of Mask R-CNN object detection technique for defect detection in stone cultural heritage Gümüşler monuments and monasteries, and showed that the model has an mAP value of 98.186% and can automatically and accurately identify nine types of defects with different color, shape and texture characteristics. The results of the study show that the model has a mAP value of 98.186% and can automatically and accurately identify nine types of defects with different color, shape and texture characteristics, ranging from a few centimeters to several meters in size, thus demonstrating the feasibility of using artificial intelligence in restoration. The results of this study showed that cropping the images to an appropriate resolution, without categorizing them by color or contour, significantly improved the detection of peeling damage on wall paintings. Scholars [4] Automatic detection of flaking damage on wall paintings using the YOLOv4 object detection method the results show that the YOLOv4 method is effective in detecting the peeling damage of murals and has better results for small targets with high recall and high accuracy. Scholars [5] applied YOLOv5 and Mask R-CNN to detect and identify Balinese carvings, and the results showed that both object detection methods have their advantages in detecting Balinese carvings. Scholars [6] applied the YOLOv5 method to identify the defects of thangka images, and the experimental results showed that the YOLOv5 method can effectively identify the defects of thangka paintings. Scholars [7] applied the YOLOv5 method to identify defects in thangka images, and the results of the study showed that YOLOv5 could detect multiple defects simultaneously, proving the effectiveness and reliability of the YOLOv5 object detection technique. Scholars [8] proposed a YOLOv5-based damage detection algorithm for cave wall paintings. The results of this study showed that the method solved the drawbacks of the cave wall painting manual inspection process which was tedious and had low accuracy, and the study also proved that the YOLOv5 network is effective for damage detection.

The results of the literature also show that the use of object detection methods can effectively help in the field of restoration marking, and the YOLO object detection technology, after continuous improvements and updates, has also shown significant results and improvements in terms of real-time computation and accuracy. Therefore, this study will use YOLOv5 object detection technology to identify the types and locations of missing objects, reduce the restorer's condition inspection time, and improve the restorer's operational efficiency.

III. METHOD

In this study, the common defects in the restoration of oil paintings were identified as indicators, with Retouching and Insect Excrement as the main objects. The image data for this study were used with the permission of the Chen Cheng-Po Cultural Foundation and the Cheng Shiu University Conservation Center. The process is described as follows: the collected image data is processed and classified with defects, and do data augmentation for the data set samples, and the image data is labeled using LabelImg image labeling software, and the data set is partitioned into 8:2 and input to YOLOv5 training model, and finally the model is evaluated for its performance.

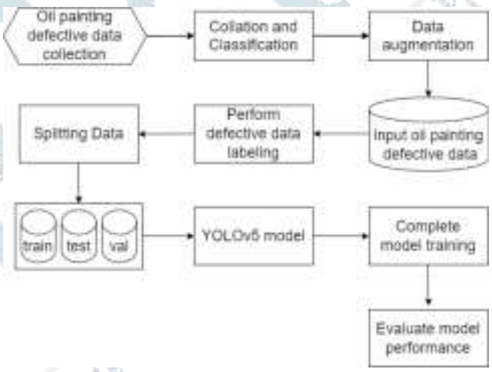

Figure 2. Processing flow chart

A total of 45 oil paintings were included in this study, 35 provided by the Chen Cheng-Po Cultural Foundation and 10 provided by the Cheng Shiu University Conservation Center of which samples were photographed in the actual working environment of the restorers. total of 1150 samples of the original available datasets and one image of the complete work will be kept in the data set. The non-destructive detection light sources used are UV and normal light. reason for not choosing infrared light and X-rays is that infrared light is mostly used to check the sketches of the base, while X-rays are used to check whether there are any hidden objects in the drawing. This study will also use the traditional geometric change data augmentation method to enhance the image data for the defects of the painted layer. The function of image data augmentation is that it can compensate for the overfitting problem caused by insufficient data sample size. In this study, the original image data will be rotated, scaled, scaled, blurred, or flipped horizontally and vertically, and so on. This method increases the number of samples in the dataset by outputting the expanded image for the type or image data to be manipulated and allows the model to do a learning process. The relevant light source applications were selected as shown in Table I, The identified categories are shown in Table II, Figures 3 to 4 show the sample selection examples for the study. Figures 5 to 6 show the sample of data augmentation.

Table I：Non-destructive light selects for data sets.

Normal light	UV light	Infrared light	X-rays
✓	✓		

Table II：Data Set Defect Type and Quantity.

Defect Type	Retouching image	Insect exclusion images
Quantity	585	565

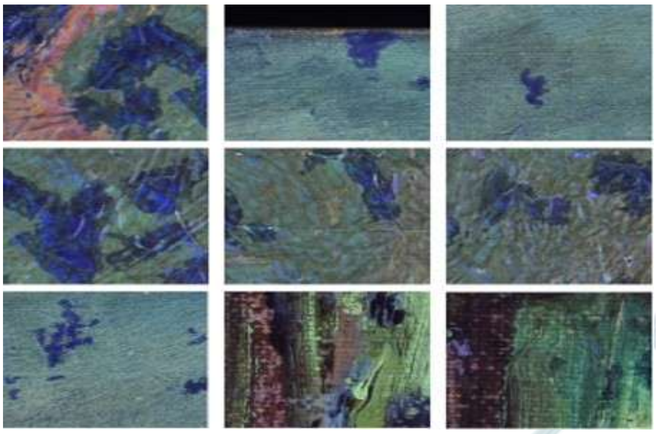

Figure 3. Retouching training samples.

Figure 4. Insect exclusion training samples.

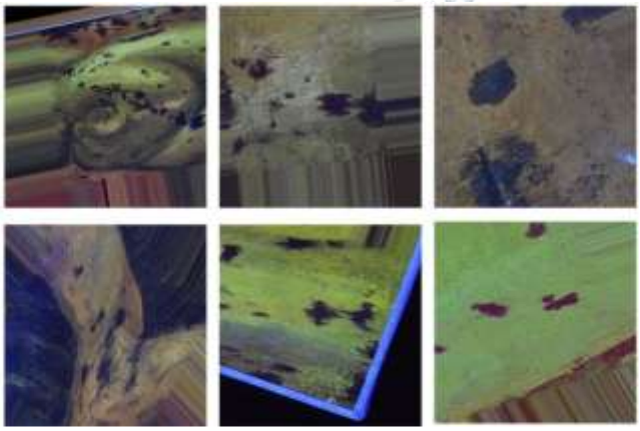

Figure 5. Retouching data augmentation.

Figure 6. Insect exclusion data augmentation.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

This study was conducted to detect defects in the oil painting layers, and the defects detected were retouching and insect exclusion, using an experimental environment with Windows 10 system, Python 3.8, and Google Colab Pro to build the YOLOv5 model. The photos of the dataset were all taken from the actual environment of the restoration operation, and the defects were taken with a digital camera. The image size was 640*640 during training. The study used a total of 1150 samples of oil painting layers defects detected and split them 8:2 for training and experimented with the performance of the data set with and without data augmentation. It was found that the data on this dataset with geometric data augmentation was better than without it. Table III shows the performance before data augmentation. Table IV shows the performance after data augmentation.

Table III： Before data augmentation performance.

Class	Precision	Recall	mAP (@0.5)	mAP (@0.5:0.95)
All	0.753	0.602	0.64	0.463
Retouching	0.651	0.562	0.554	0.311
Insect exclusion	0.856	0.643	0.727	0.615

Table IV：After data augmentation performance.

Class	Precision	Recall	mAP (@0.5)	mAP (@0.5:0.95)
All	0.880	0.69	0.783	0.623
Retouching	0.832	0.654	0.708	0.563
Insect exclusion	0.929	0.726	0.858	0.683

It can be found that the performance of Retouching has improved significantly, with an increase of about 15.4% in mAP. The reason for this is that the original dataset, in which most of the defective pictures are taken by dividing the whole oil painting into four parts, and the larger size of the artwork

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causes distortion of the defects and the problem of too small size, which leads to poor training performance.

To solve this problem, this study uses data augmentation methods of cropping and geometric data augmentation to improve the performance of each data. The original Insect exclusion class was also improved by data augmentation, with a 13.1% improvement in mAP compared to the previous one. This also illustrates that using data augmentation in this dataset can effectively improve the performance of model detection. This is the preliminary result of this study. In this study, the sample size of the data set is relatively small, so more data will be collected for the training of relevant models. Also, suitable data augmentation methods will be selected for the type of defects, so that the model performance can be better improved. After discussions with the restorers, the YOLOv5 model proposed by the Institute can initially help the restorers in detecting the defects of oil paintings, and it has improved the detection time, and also detected and marked some defects that the restorers missed. Figures 7 to 8 showing the results of using YOLOv5 to assist the restorer in the detection of oil painting defects.

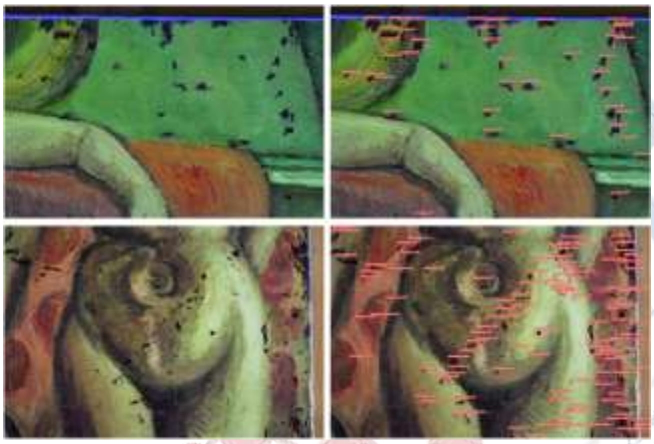

Figure 7. Retouching inspection results.

Figure 8. Insect exclusion inspection results.

V. CONCLUSION

This paper proposes to use the YOLOv5 object detection model to assist restorers in optimizing the working hours for the process of viewing the condition of oil paintings under restoration, and to detect defects in oil paintings, effectively reducing the restorer's working time by using object detection technology, and assisting the defect marking and condition type description operations to improve the effectiveness of artwork restoration and reduce time cost and labor waste. In the future, we will add more categories of oil painting defects and apply the model to embedded devices to enhance the effectiveness of the actual application.

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