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Advancing Museum Artifact Recognition: Reflection Removal and Fine-Grained Classification for Superior Visitor Experience

Yu-Hxiang Chen, Chen-An Chan, Gao-Ruei Chang, Yong-Syuan Chen, Ting-Ting Chang, Yu-Ting Li, and Chia-Yu Lin
Department of Computer Science and Information Engineering, National Central University, Taoyuan, Taiwan
Corresponding Author: Chia-Yu Lin (sallylin0121@ncu.edu.tw)

***Abstract*—Traditional museum guidance systems often rely on QR code scanning, which can hinder low-light conditions and visual obstructions. A more practical alternative is direct artifact photography; however, challenges such as reflections, blurriness, and occlusions frequently impair accurate artifact recognition. This paper proposes an advanced museum artifact recognition system integrating an LSTM-based reflection removal technique, image enhancement methods, and a fine-grained artifact classification model. The proposed workflow effectively reduces reflection interference, enhances image quality, and improves object recognition accuracy. Experimental results demonstrate the system's strong potential in enhancing museum guide systems, significantly improving the visitor experience through more reliable and interactive artifact recognition.**

***Index Terms*—Fine-grained classification, reflection removal, museum guidance**

I. Introduction

Traditional museum guidance relies on QR code scanning, numeric input, or Beacon positioning. Still, these methods often struggle in low-light conditions, and their effectiveness is further limited when QR codes are too small to scan reliably or Beacon positioning has a restricted range. With mobile devices now capable of direct artifact recognition, AI-based techniques offer a more seamless experience. However, AI-based recognition struggles with glass reflections, blurriness, and occlusions, which reduce image clarity and artifact recognition accuracy.

Previous studies have explored various approaches to address these challenges. Zhang et al. [1] proposed automatic exposure adjustments to enhance object recognition but faced detail loss and misclassification due to exposure variations. Yousif [2] applied preprocessing techniques such as normalization and random cropping, improving general accuracy but failing to address reflection-related distortions specifically. Ni et al. [3] leveraged Light Field (LF) cameras for reflection removal, achieving superior accuracy; however, LF cameras remain impractical for museum visitors relying on smartphones.

We propose an enhanced reflection removal module to overcome these limitations, optimizing Li et al.'s method [4] with an image quality enhancement module. Using the High-temperature Refinement and Background Suppression model (HERBS) [5] for fine-grained classification, our system maintains a lightweight design and accuracy under reflective conditions. Experiments show that our approach reduces recognition errors, enhances visitor experience, and improves artifact recognition stability across varying lighting conditions.

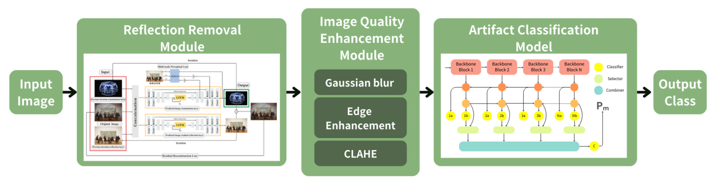

Fig. 1. System architecture.

II. Methods

To ensure artifacts are accurately and promptly recognized, the system requires comprehensive data preprocessing to restore images affected by reflections or blurriness, enabling the model to learn artifact features better. The system architecture, as shown in Fig 1, consisted of three steps: A) Reflection Removal Module, B) Image Quality Enhancement Module, and C) Artifact Classification Model.

A. Reflection Removal Module

As shown in Fig 2, our module builds upon the reflection removal method of Li et al.'s reflection removal method [4]. It begins by extracting features using convolutional layers, followed by ReLU activation. These features are fed into generative networks that predict the transmission and reflection layers. These networks incorporate LSTM units to model the iterative refinement process, treating each iteration as a sequential time step. This structure allows the network to retain and utilize important features learned in previous iterations. The networks produce a transmission layer T' and a residual reflection layer R', which are auxiliary inputs to improve accuracy in subsequent iterations.

B. Image Quality Enhancement Module

After reflection removal, we mitigate blurriness caused by uneven lighting and hand tremors, which degrade artifact recognition accuracy. We apply Gaussian blur to smooth high-frequency noise, edge enhancement to restore sharpness, and Contrast-limited adaptive histogram equalization (CLAHE) [6] to improve local contrast while preventing noise amplification. These enhancements refine image quality and contribute to more accurate classification and recognition.

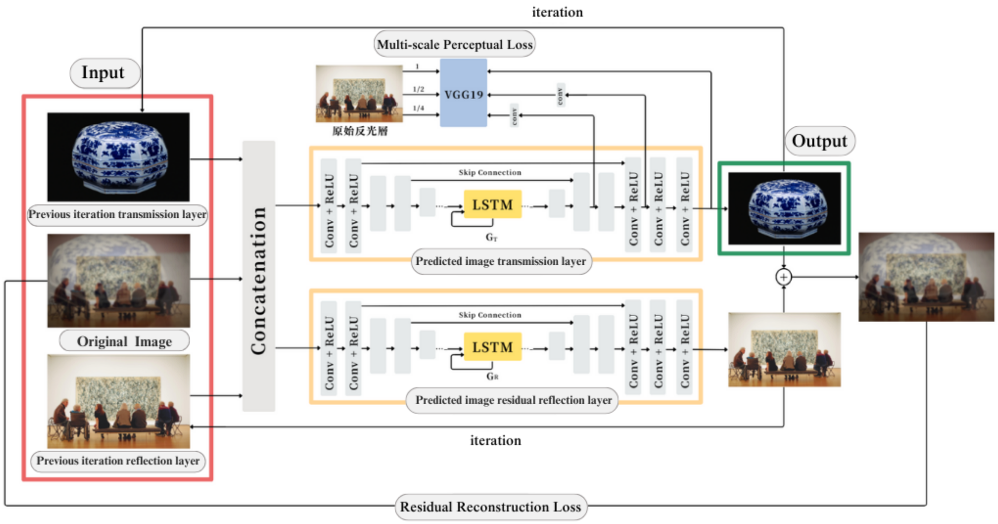

Fig. 2. The architecture of the Reflection Removal Module.

(a)original image (b) reflection removal image (c) quality enhance image

Fig. 3. Results of processing images.

C. Artifact Classification Model

To classify fine-grained artifact variations, we adopt the HERBS model [5], which integrates a high-temperature refinement module for multi-scale feature learning and a background suppression module to filter irrelevant noise. We employ a Transformer backbone to enhance feature extraction, leveraging self-attention to capture long-range dependencies and improve classification accuracy.

III. Experiment Result

We collect a dataset of 748 museum artifact images, comprising 700 images captured with a digital single-lens reflex (DSLR) camera and 48 images taken with a smartphone. All images are resized to 512×512 pixels before being fed into the model. The experiments are conducted on an NVIDIA RTX 3080 GPU, using Top-1 accuracy as the evaluation metric.

Fig. 3 shows processed images with significantly reduced reflections and blurriness. The model achieves 100%

IV. Conclusion

This study proposed an artifact recognition system integrating reflection removal, image enhancement, and the HERBS model for fine-grained classification. The system effectively mitigates reflection interference and adapts to varying lighting conditions by leveraging these techniques. Experimental results demonstrated its robustness, achieving 100% accuracy on smartphone images and 99.7% on DSLR images, highlighting its reliability for museum guidance and enhancing the visitor experience.

Future improvements could use K-means clustering to pre-classify images before assigning them to the most suitable HERBS model. This method improves accuracy by reducing misclassifications and lowers computational costs by avoiding retraining the entire dataset.

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