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An Intelligent Color-Difference Detection System for Automotive Refinishing based on YOLOv8 and OpenCV

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Abstract

Manual color-difference assessment in automotive refinish color matching is highly subjective, and existing inspection methods are poorly suited to high-quality invisible repairs. We therefore developed an intelligent color-difference detection system based on YOLOv8 and OpenCV, integrating automatic paint-surface localization, human-in-the-loop sampling as a fallback for missed detections, ΔE-based color-difference quantification, and automated three-tier color-matching recommendations. In invisible-repair scenarios, the system raised the inspection completion rate from 43% to 100%, and its quantified color-difference results met workshop quality-inspection requirements. The system thus provides a practicable route to standardizing and quantitatively managing color matching in automotive refinishing.

Keywords

YOLOv8; OpenCV; Color-difference Detection; CIE-LAB; Automotive Refinishing.

1. Introduction

Growth in vehicle ownership has expanded used-car refurbishment and the repair of paint finishes on accident-damaged vehicles, making color matching a core operation in automotive repair. Conventional matching relies on a technician's visual judgment and is thus beset by subjectivity, frequent rework, and variable quality control; the expertise of skilled colorists is also largely tacit and difficult to transfer. Machine-vision methods based on color-threshold discrimination, meanwhile, cannot reliably localize the repair region in high-quality refinishing[1].

This study therefore develops an intelligent color-difference detection system for automotive refinishing based on YOLOv8 and OpenCV. YOLOv8 localizes the original equipment manufacturer (OEM) and repaired finishes; when a detection is missed, OpenCV invokes manual bounding-box selection as a fallback. The CIE-LAB space is then used to compute an overall color difference and output tiered color-matching recommendations. Coupling automated detection with human interaction, the system addresses a persistent industrial difficulty-that invisible repairs are hard to detect and quantify-while reducing the waste from repeated trial spraying and improving matching quality and process optimization. Being self-contained and inexpensive to retrofit, it can be packaged for direct deployment.

2. Theoretical Background and Methods

2.1 YOLOv8 Object Detection

YOLO (You Only Look Once) is a classic one-stage object detection algorithm that predicts object locations and categories directly through a single convolutional neural network, offering fast inference and low deployment cost, and is therefore well suited to industrial inspection

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scenarios[2].YOLOv8 strengthens feature extraction through the C2f module and supports model variants of multiple sizes, balancing accuracy and speed[3].

Given the limited sample size of the vehicle-paint dataset used in this study, a transfer learning strategy was adopted[4], in which YOLOv8 pretrained weights from the COCO dataset were loaded for fine-tuning, enabling the network to identify task-specific features such as paint seams and polishing marks on the basis of the general visual features already learned. The YOLOv8 model was selected in order to achieve a balance between detection accuracy and inference speed.

2.2 CIE-LAB Color Space and Color-Difference Quantification

Accurate quantification of paint color difference depends on the choice of an appropriate color space. The commonly used RGB color space describes color through the additive superposition of the intensities of the red, green, and blue channels. Its channels are strongly correlated with one another, and its color distribution is non-uniform-equal numerical differences in different color regions do not correspond to equal differences in human perception. Computing color difference directly in RGB therefore poorly reflects true visual perception and is readily affected by the illumination conditions at image capture.

CIE-LAB is a uniform color space established by the International Commission on Illumination (CIE), comprising a lightness channel L and two chromaticity channels, a and b. The L channel ranges from 0 to 100 and represents the lightness of a color; positive values of a point toward red and negative values toward green, while positive values of b point toward yellow and negative values toward blue[5], as shown in Figure 1.

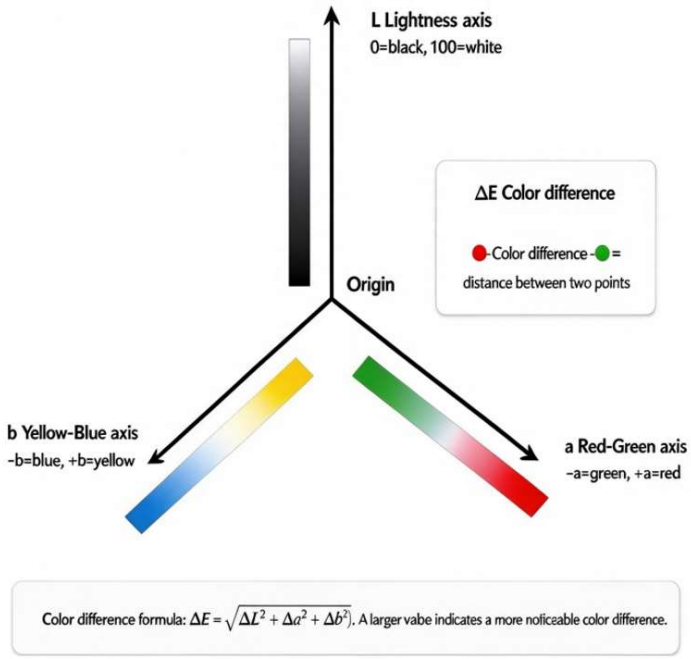


Figure 1. Schematic illustration of the CIE-LAB color space

Because the Euclidean distance between colors in this space corresponds closely and linearly to perceived color difference, it has been widely applied to color-difference inspection and quality control in industry.

In the CIE-LAB space, the overall color difference ΔE between two paint surfaces is calculated using the Euclidean distance formula:

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$$\Delta E = \sqrt{(L_1 - L_2)^2 + (a_1 - a_2)^2 + (b_1 - b_2)^2}$$

Where (L1,a1,b1) and (L2,a2,b2) are the mean L, a, and b values of the OEM finish and the repaired finish, respectively[6][7].

According to general standards in the automotive coating industry, the color difference is classified into three grades based on ΔE, with the corresponding process recommendations given in Table 1.

Table 1. Color-difference grading based on ΔE and corresponding process recommendations.

ΔE Range	Human visual perception	Judgment	Process suggestion
ΔE ≤3	Barely distinguishable	Acceptable	The current formula can be archived as a standard sample
3< ΔE ≤ 8	Slightly perceptible	Fine-tuning required	Adjust the pigment ratio according to LAB channel deviations
ΔE >8	Obvious color difference	Unacceptable	Discard the current formula and re-formulate

Based on this grading standard, the present study establishes a color-matching process recommendation mechanism, thereby linking quantitative detection to process guidance.

2.3 Overall System Architecture

The overall workflow of the two-layer detection system established in this study is shown in Figure 2. Once the system receives a captured vehicle-paint image, the YOLOv8 model is used to automatically identify the OEM and repaired paint regions. If the repaired region is successfully detected, sampling proceeds directly; if detection fails because the repair marks are not sufficiently distinct, a human-interactive bounding-box selection is triggered as a fallback. After the ROI regions are output from these two paths, OpenCV converts them to the CIE-LAB space, the overall color difference ΔE is then calculated, and color-matching recommendations are finally output according to the grading standard and the results are saved.

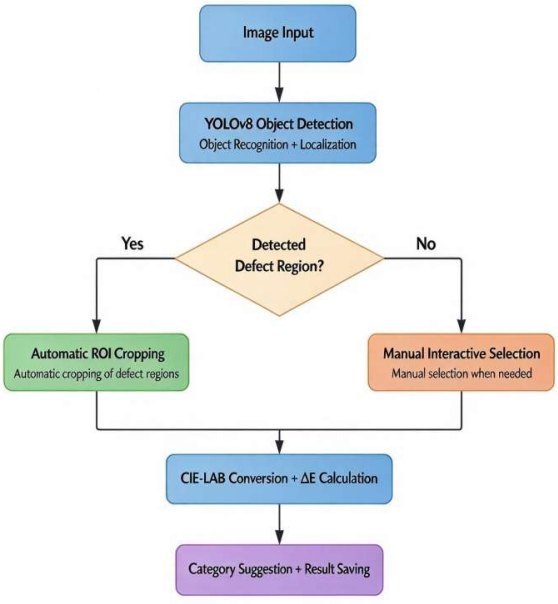


Figure 2. Overall system workflow.

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3. Design of Key System Modules

3.1 Dataset Construction and Model Training

3.1.1. Image Acquisition and Annotation

The experimental images in this study were acquired at the Yuantong Used Car Repair Shop in Linyi, Shandong. The imaging environment was maintained under fixed indoor lighting and fixed camera parameters to reduce the interference of illumination fluctuation with color detection. The samples covered three typical repair grades: poor-quality repairs with highly pronounced color differences, ordinary repairs with slight color differences, and high-quality invisible repairs whose boundaries are difficult to distinguish by eye. Rectangular bounding boxes were annotated using the X-AnyLabeling tool, with two classes defined: "original-paint," denoting the OEM finish, with class ID 0, and "repair-paint," denoting the repaired finish, with class ID 1, as shown in Figure 3.

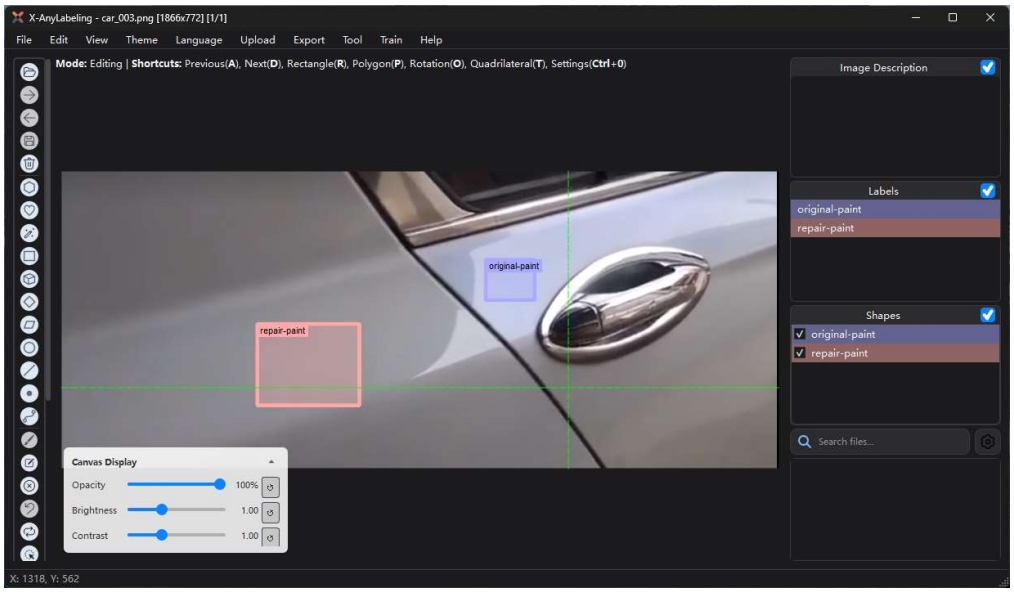


Figure 3. Example of dataset annotation

The annotation principle was as follows: any repainted region was annotated regardless of the magnitude of its color difference, so as to guide the model to learn multidimensional features such as paint seams, polishing texture, and orange-peel marks, rather than relying solely on color difference for identification.

3.1.2. Model Training

The YOLOv8s pretrained weights were fine-tuned on the self-constructed vehicle-paint dataset via transfer learning. Training used 640 × 640 inputs, 50 epochs, a batch size of 8, an initial learning rate of 0.01, the Adam optimizer, and a confidence threshold of 0.6, with random flipping, brightness perturbation, and mosaic augmentation applied to improve generalization. The weights achieving the highest mAP50 on the validation set were retained as the final detection model.

3.2 Automatic Paint-Region Detection Module based on YOLO

This module localizes and classifies paint regions without human intervention. Each input image is resized to the network input size and fed to YOLOv8 for inference, which outputs the class probability, confidence, and coordinates of each candidate box. After non-maximum suppression (NMS), boxes exceeding the confidence threshold are retained. The system then extracts the bounding-box coordinates of the OEM and repaired finishes by class ID and crops the corresponding ROIs from the original image. If both classes are detected, automatic detection is judged successful and the process proceeds directly to color-difference calculation. The module thus handles repairs with pronounced marks and large seam or texture differences fully automatically.

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3.3 Human-in-the-Loop Fallback Sampling Module

Because YOLO frequently fails to detect the repaired region in high-quality invisible repairs, a human-in-the-loop fallback module was designed as a fault-tolerance mechanism. If inference returns no "repair-paint" class, or only the OEM finish, OpenCV's "selectROI" window prompts the operator to select the OEM and repaired regions in turn; the operator drags a rectangle and presses Enter to confirm, or ESC to cancel. The system then crops both ROIs from the original image using the selected coordinates.

The module matters because, where deep learning fails on weak features, human–machine interaction preserves the integrity of detection and extends the system's applicability across repair qualities—one of this study's core innovations.

3.4 Color-Difference Quantification and Graded Recommendation Module

Regardless of whether the ROI is obtained through automatic detection or through human fallback, the system uniformly executes the color-difference calculation procedure. The ROI is first subjected to Gaussian blurring to suppress highlight noise, and is then converted to the CIE-LAB space, where the mean L, a, and b values are calculated and ΔE is derived.

The calculation method and grading standard for ΔE are as described in Section 2.2. The system automatically outputs the corresponding color-matching recommendations according to ΔE, and simultaneously saves the detection result images and data logs locally.

4. Experimental Results and Analysis

4.1 Experimental Environment and Dataset

The experiments in this study were conducted in a specific hardware and software environment. The CPU was an Intel Core i7-14650HX with 32 GB of memory, and the operating system was Windows 11. The deep learning framework was PyTorch 2.13.0, the object detection library was Ultralytics 8.4.117, the image processing library was OpenCV 5.0.0, and the numerical computation library was NumPy 2.5.2.

The experimental dataset was derived from vehicle-paint images acquired on site in the workshop and comprised three types of samples-pronounced color difference, slight color difference, and invisible repair-totaling 86 images, of which 66 formed the training set and 20 the validation set. All images were acquired under similar external conditions to ensure the consistency and comparability of the color information.

4.2 Performance Analysis of the YOLO Detection Model

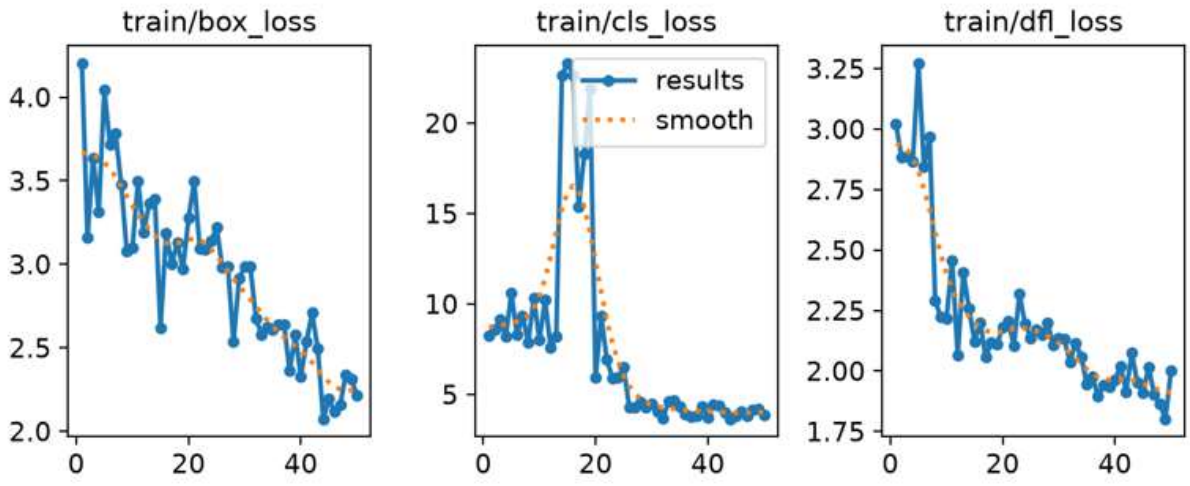


Figure 4. Model training loss curves

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After training was completed, performance was evaluated on the validation set using mean average precision (mAP), precision, and recall as evaluation metrics. The loss curves during training are shown in Figure 4. As the number of training epochs increased, both the training and validation losses decreased gradually and tended toward convergence, indicating that the model learned effectively.

The final performance metrics of the model are given in Table 2, in which mAP50 reaches 63%, precision is 88%, and recall is 75%.

Table 2. Final performance metrics of the YOLO model

Metric	mAP50	Map50-95	Precision	Recall
Value	63%	32%	88%	75%

Analysis by repair grade shows that the model detected samples with pronounced color differences and clear seams reliably, and still detected slight-color-difference samples via texture and edge features. For high-quality invisible repairs, however, the repaired region closely resembles the OEM finish in both color and texture, so recall decreased and some samples went undetected. This verifies the necessity of the human fallback mechanism: automatic detection alone cannot cover invisible repair scenarios.

4.3 Color Difference Verification Test

To verify the effectiveness of the system's color-difference quantification function, three representative groups of samples were selected: samples with pronounced color differences ($\Delta E>8$), samples with slight color differences ($3<\Delta E\leq 8$), and invisible repair samples ($\Delta E\leq 3$). Detection was carried out for each group, and the L, a, and b parameters, ΔE values, detection methods, and process recommendations were then recorded. The detailed results are presented in Table 3.

Table 3. Results of variable regression analysis

Sample group	OEM paint LAB	Touch-up paint LAB	ΔE	Process recommendation
Obvious color difference	(62.49,0.71,-2.18)	(82.77,2.19,-13.24)	23.15	Color difference out of specification; re-formulate
Slight color difference	(58.32,1.45,-5.67)	(55.10,3.21,-8.45)	5.82	Minor color deviation; fine-tune the formula
Seamless touch-up painting	(70.15,-0.82,3.56)	(69.48,-0.35,4.12)	1.03	Acceptable color matching

Examples of the detection results are shown in Figure 5, where the region marked by the green box corresponds to the OEM finish and the region marked by the red box corresponds to the repaired finish. For invisible repair samples, if YOLO does not detect the repaired region, the system automatically activates manual bounding-box selection as a fallback, with the prompt shown in Figure 6. The color-difference calculation is finally completed, demonstrating the effectiveness of the two-layer mechanism in complex scenarios.

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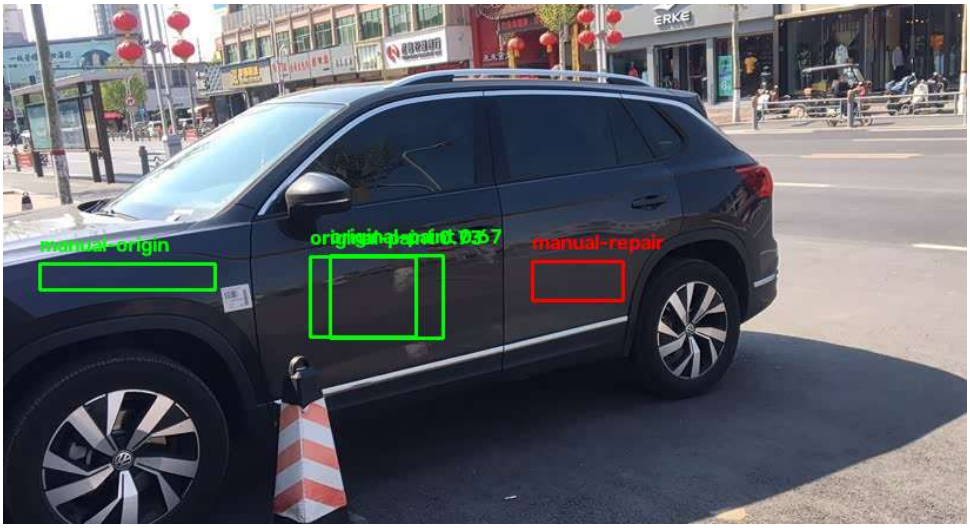


Figure 5. Example of detection results.

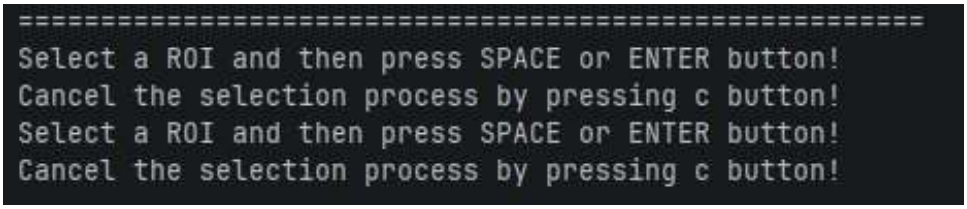


Figure 6. Illustration of manual bounding-box selection as a fallback.

4.4 Effectiveness Analysis of the Two-Layer Fault-Tolerance Mechanism

To further verify the value of the two-layer fault-tolerance mechanism, this study compared the detection completion rate of two schemes in invisible repair scenarios: "YOLO automatic detection alone" and "YOLO plus manual fallback." Fourteen invisible-repair samples were tested, and the results are shown in Table 4.

Table 4. Comparison of detection completion rates between the two schemes

Scheme	Number of successful samples	Completion rate
YOLO-only automatic detection	6	43%
YOLO with manual fallback mechanism	14	100%

As Table 4 shows, when YOLO was used for automatic detection alone, numerous missed detections occurred in invisible repair scenarios, and the detection completion rate was only 43%. After the human fallback mechanism was introduced, color-difference detection could be completed for all samples, and the detection completion rate rose to 100%. These results indicate that the two-layer fault-tolerance mechanism addresses the industrial difficulty of automatically identifying high-quality invisible repairs and improves the applicability and robustness of the system.

5. Application to Color-Matching Process Optimization

5.1 Conventional Workflow and Its Limitations

Conventional color matching relies on the technician's experience: a formulation is mixed, trial-sprayed, and compared by eye, with repeated trial and error. This practice is subjective in judgment, prone to rework, and produces formulations that are difficult to codify.

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5.2 Color-Difference-Based Process Optimization Scheme

To address these problems, the two-layer fault-tolerant color-difference detection system was introduced into refinish color-matching quality inspection, yielding three measures.

(i) Quantified quality criteria. ΔE replaces visual judgment as the objective criterion of repair quality, with three grades: $\Delta E \leq 3$ acceptable, $3 < \Delta E \leq 8$ requiring minor adjustment, and $\Delta E > 8$ unacceptable.

(ii) Standardized workflow. A machine-vision inspection node is inserted into the conventional "mix–trial-spray–compare" loop, so that an image is captured and ΔE computed after each trial spray, and the resulting recommendation, together with the per-channel L, a, and b deviations, guides the subsequent tint adjustment.

(iii) Formulation archive. Each accepted formulation is stored with its ΔE value and vehicle color information in a searchable database, so that a historical formulation can be retrieved directly for a repair of the same color, reducing repeated trials.

These measures are expected to reduce rework, lower paint consumption, shorten the per-vehicle repair cycle, and improve the consistency and standardization of repair quality. Table 5 compares the conventional and optimized workflows.

Table 5. Comparison between traditional and optimized color matching processes

Comparison dimension	Traditional color matching process	Optimized color matching process
Color difference discrimination	Subjective visual comparison by human eyes, no quantitative basis	Machine vision detection, output quantitative ΔE value
Basis for color matching	Relies on individual experience of technicians, blind trial and error	Refer to historical formulas and LAB channel deviations for targeted adjustment
Acceptance criterion	Varies from person to person, no unified threshold	$\Delta E \leq 3$ is acceptable; the standard is unified and repeatable
Rework characteristics	Rematch entirely once color difference fails, repeated trial spraying (usually 3–5 times)	Fine-tune pigment slurry according to ΔE and LAB deviations (usually 1–2 times)
Operator dependence	Highly dependent on senior technicians; quality affected by personnel changes	Standardized workflow reduces experience dependence, operable for novices
Material and working hour	Multiple trial sprays lead to paint waste and working-hour consumption	Reduce rework frequency, cut material waste and maintenance cycle

6. Conclusion

Manual color-difference assessment in automotive refinish color matching is highly subjective, and existing inspection methods adapt poorly to high-quality invisible repairs. This study therefore developed an intelligent color-difference detection system based on YOLOv8 and OpenCV, in which YOLOv8 identifies the OEM and repaired finish regions and human-interactive bounding-box selection supplements missed detections. After conversion to the CIE-LAB space, the overall color difference ΔE is computed and graded color-matching recommendations are output. In invisible repair scenarios, the system raised the detection completion rate from 43% to 100%, and its quantified ΔE results can replace subjective visual judgment while meeting workshop quality-inspection requirements.

Rather than pursuing full automation, the system covers paint finishes of different repair qualities through human–machine collaboration, offering a quantitative tool and a standardized reference for

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refinish color matching. Future work will expand the sample size, improve the identification of subtle color differences, and link the results to a formulation database to close the loop of "detection–color matching–verification."

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