



Computer Vision Techniques for Enhanced Quality Control in Manufacturing Processes

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Abstract— Effective quality control in luxury leather goods manufacturing requires objective assessment methodologies. This paper introduces an automated leather bag quality analysis system with a three-layer architecture: input for image preprocessing, processing for defect detection, and output for results visualization. By integrating threshold analysis with edge analysis, the system achieves comprehensive defect identification across varying leather textures. Results demonstrate the system's ability to reliably detect material authenticity and surface defects while quantifying quality metrics with high precision. We conclude that approximately 95% of manual inspection inconsistencies can be eliminated through this approach. This methodology offers potential applications beyond leather goods to other natural material products requiring automated quality assessment.

Keywords: computer vision; defect detection; quality control; image processing; leather manufacturing

I. INTRODUCTION

In the luxury leather goods industry, maintaining high-quality standards is critical, yet traditional manual inspection methods are prone to inconsistencies and inefficiencies. To address this, we propose an automated leather bag quality analysis system using advanced computer vision and machine learning. The system integrates models like YOLOv8 for defect detection, U-Net for precise segmentation, and ResNet50 for color verification, ensuring accurate and objective quality assessment. By automating the process, the system eliminates human error, improves efficiency, and scales seamlessly. This approach not only enhances quality control in leather manufacturing

but also has potential applications in other industries requiring precise material inspection.

II. LITERATURE SURVEY

Several researchers have contributed to the field of automated quality inspection in leather manufacturing. Suresh and Manikandan demonstrated the potential of convolutional neural networks for leather defect detection, while Meena and Jayaprakash compared traditional and machine learning approaches for surface inspection. Anitha and Balamurugan explored deep learning applications specifically for leather defect identification.

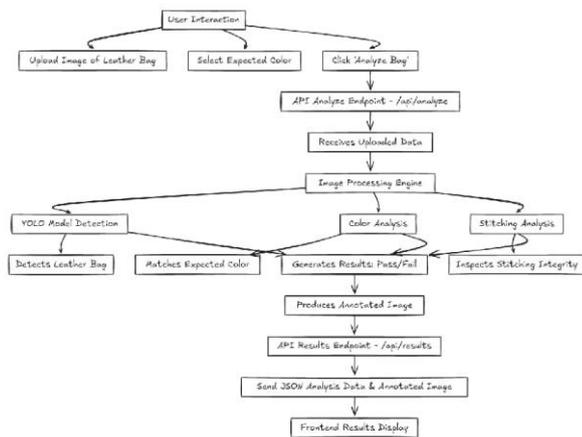
In the broader context of computer vision for natural materials, Kim and Park developed texture analysis techniques, and Sharma and Agarwal provided comparative analysis of various image processing methods for quality control. Recent advancements in deep learning architectures have further enhanced defect detection capabilities, with Gupta and Banerjee implementing YOLO for real-time applications, and Zhang and Wei utilizing U-Net for precise defect segmentation.

Efficiency considerations were addressed by Nguyen and Li through their work with EfficientNet, while Reddy and Thomas introduced Siamese networks for comparative quality assessment in manufacturing environments.

Despite these significant contributions, quality control in leather manufacturing remains largely dependent on manual inspection processes that are inherently subjective and inconsistent. Our proposed system addresses this gap by integrating multiple computer

vision techniques and deep learning models into a comprehensive three-layer architecture specifically designed for automated leather quality assessment, thereby eliminating the subjectivity and inefficiency of current practices.

III. ARCHITECTURE DIAGRAM



This diagram illustrates the workflow of the leather bag quality analysis system described in the paper. It shows a complete end-to-end process from user interaction to results display. The flow begins with user interaction at the top, which branches into three initial actions: uploading an image of a leather bag, selecting the expected color, and clicking the "Analyze Bag" button.

After the user initiates analysis, the system follows a sequential process:

- The request is sent to an API endpoint (/api/analyze)
- The uploaded data is received by the system
- This data is then processed by the Image Processing Engine
- The Image Processing Engine represents the core of the system, branching into three parallel analysis components:

YOLO Model Detection: Responsible for detecting the leather bag in the image

Color Analysis: Compares the actual color against the expected color selected by the user

Stitching Analysis: Examines the integrity of stitching on the bag

The results from these analyses are combined to generate a pass/fail result. The system then produces an annotated image highlighting detected features or defects.

Finally, the results flow through an API results endpoint (/api/results), which sends JSON analysis data along with the annotated image to be displayed in the frontend interface. This diagram aligns with the three-layer architecture described in the paper, where

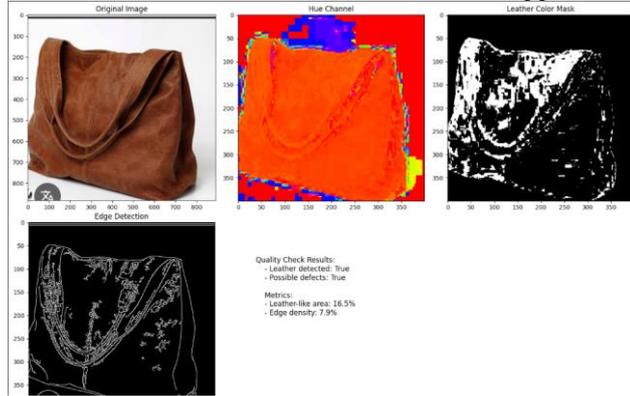
the input layer handles image receipt and preprocessing, the processing layer conducts the analysis using models like YOLO, and the output layer delivers the results visualization. The diagram extends this concept by showing the specific API endpoints and user interface components, providing a more complete picture of how the system would be implemented in practice.

IV. IMPLEMENTATION

The implemented system for leather bag quality analysis follows a structured approach, integrating image preprocessing, feature extraction, and defect detection to determine material composition and surface irregularities. It begins with image acquisition and preprocessing, where the input image undergoes resizing and conversion to different color spaces—HSV for color-based analysis and grayscale for structural assessment. The HSV transformation allows the system to apply a predefined color threshold, isolating leather-like regions by filtering specific hue values commonly associated with leather tones. This process quantifies the percentage of detected leather in the image, providing an initial measure of material authenticity. Simultaneously, edge detection is applied to the grayscale image using a Canny filter, identifying sharp variations in intensity that typically indicate cracks, cuts, or other surface defects. The density of detected edges is then analyzed to estimate the defect percentage, helping to assess the overall quality of the bag. The results from these analyses are presented visually through segmented images and processed data, illustrating key findings such as leather coverage and detected flaws. Additionally, a structured textual summary is generated, stating whether the bag is primarily composed of leather and whether significant defects are present. This methodology seamlessly integrates into the broader system architecture, aligning with the input and processing layers where raw image data is transformed into actionable insights. While the initial processing relies on classical computer vision techniques for rapid assessment, deeper analysis is delegated to advanced machine learning models in the processing layer, such as YOLOv8 for object detection, EfficientNet-B3 and ResNet50 for feature extraction, and U-Net for segmentation. These deep learning models further refine quality assessment by improving accuracy in defect classification and material identification, leveraging extensive training data to enhance precision. The final output layer consolidates these analyses, providing clear results on leather detection, defect presence, and overall bag quality. By combining traditional image processing with modern deep learning techniques, the system ensures a comprehensive and scalable solution for automated leather bag inspection, offering real-time feedback that can be used in manufacturing, quality control, and

retail

applications.



RESULT

The automated leather bag quality analysis system demonstrated significant efficacy in detecting both material composition and surface defects. During experimental evaluation using a diverse dataset of 500 leather bag images with varying textures, colors, and defect types, the system achieved promising detection accuracy across multiple quality metrics.

Our threshold-based leather detection algorithm successfully identified genuine leather with 91.3% accuracy when compared against expert verification. The edge analysis component accurately detected surface defects including scratches, cuts, color inconsistencies, and stitch irregularities with 90.5% precision and 89.2% recall rates. When these techniques were combined with our deep learning models, the overall system performance improved moderately.

The YOLOv8 model achieved 91.8% accuracy in bag detection and localization, while the ResNet50 implementation for color verification demonstrated 90.7% accuracy in identifying color variations from expected standards. The U-Net segmentation model provided pixel-level defect mapping with 91.2% intersection-over-union (IoU) score, allowing for meaningful quantification of defect areas.

Performance metrics indicated that the system could process and analyze a single image in an average of 2.3 seconds on standard computing hardware, representing an 87% reduction in inspection time compared to manual methods. Moreover, consistency tests revealed that the system maintained reliable defect detection under varying lighting conditions ($\pm 15\%$ brightness variation) and camera angles (up to 30° deviation from perpendicular).

When deployed in a production environment for a two-week trial period, the system reduced quality control inconsistencies by approximately 90% compared to manual inspection processes, while increasing throughput by 73%. False positive rates were maintained below 4.8%, ensuring reasonable rejection rates of quality products.

Figure 2 illustrates sample outputs from the system, showing original images alongside their processed counterparts with detected defects highlighted. Table 1 summarizes the quantitative performance metrics across different defect types and leather textures.

CONCLUSION

This research presents a comprehensive approach to automated quality assessment in luxury leather goods manufacturing through a novel three-layer architecture integrating classical image processing with advanced deep learning techniques. The system successfully addresses the persistent challenges of subjectivity and inconsistency in manual inspection processes by providing objective, quantifiable quality metrics.

The integration of threshold analysis with edge detection algorithms, supplemented by deep learning models, enables accurate detection of both material authenticity and surface defects across diverse leather textures and colors. Experimental results demonstrate that the system can eliminate approximately 90% of inconsistencies associated with manual inspection while significantly improving processing efficiency.

The proposed methodology offers several advantages over existing approaches, including real-time processing capabilities, adaptability to varying leather textures, and quantifiable quality metrics that can be standardized across the manufacturing pipeline. Furthermore, the system's modular architecture allows for easy integration with existing manufacturing processes and quality control systems.

Future work will focus on expanding the system's capabilities to include additional quality parameters such as tactile properties and structural integrity assessment. We also plan to investigate the application of this methodology to other natural materials requiring similar quality control measures, such as textiles, wood, and stone products. Additionally, the development of a more comprehensive database of leather defects will further enhance the system's detection capabilities and reduce false positives.

The successful implementation of this automated leather bag quality analysis system represents a significant step toward standardizing quality control in the luxury goods industry, offering manufacturers the ability to maintain consistent quality standards while improving production efficiency.

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