GLASS PRODUCT QUALITY ANALYSIS USING IMAGE PROCESSING TECHNIQUES

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ABSTRACT:

This project presents an approach for detecting cracks in glass using the YOLOv8 model. The method is designed to efficiently identify cracks in various glass items, such as windows, screens, and household products. YOLOv8, known for its real-time object detection capabilities, is utilized to locate and classify cracks across different glass surfaces with high accuracy. To improve detection performance, we incorporate multi-scale feature extraction, enabling the model to capture crack details at various resolutions. The proposed system achieves robust crack detection, providing a practical solution for quality control in industries involving glass manufacturing, repair, and safety assessment. Experimental results show that YOLOv8 offers superior performance in terms of both precision and speed, making it well-suited for real-time crack detection applications.

Index terms: **Python; crack detection; yolov8;**

I. INTRODUCTION

Glass is a brittle and transparent material that is commonly used across various industries due to its unique properties. However, cracks in glass can severely affect its structural integrity and performance. Accurate and efficient crack detection is essential for ensuring the safety and reliability of glass products. Traditional methods, such as visual inspection, are often slow and prone to human error. To overcome these limitations, advanced crack detection techniques have been developed, leveraging technologies like optical imaging, acoustic methods, and thermal analysis.

Optical imaging methods, such as digital image processing and computer vision, analyse the visual characteristics of glass surfaces to detect cracks. These techniques are effective in identifying surface defects and offer a faster, more accurate alternative to manual inspection. Acoustic methods, including ultrasonic testing and acoustic emission monitoring, use sound waves to detect internal defects and discontinuities within the glass. Thermal analysis techniques, such as infrared thermography, can detect temperature variations on the surface of the glass, revealing areas of stress concentration that may indicate cracks.

The choice of crack detection method depends on factors such as the type and size of the cracks, the specific application of the glass product, and the required accuracy. By employing these advanced techniques, cracks in glass can be detected early, preventing catastrophic failures and ensuring the safety of glass-based products.

Regular inspections are usually part of building maintenance in order to evaluate the structural state and spot possible problems. Building cracks are an obvious indicator of structural distress and are essential for estimating a structure's lifespan. However, because of accessibility problems and human error, manual inspections are frequently unreliable.

For accurate and efficient crack detection, modern technologies like YOLO (You Only Look Once) version 8, an advanced object detection algorithm, can be employed. YOLO v8 is capable of detecting cracks in glass and other surfaces with high precision in real-time, reducing reliance on manual inspection. By using deep learning models and computer vision, YOLO v8 can quickly identify and classify cracks, even in complex environments, providing a robust solution for automated crack detection. This technology allows for faster inspections and more accurate assessments, ensuring that defects are detected at early stages and preventing further damage.

In various industries, including aerospace and military applications, materials are subjected to extreme conditions such as high overload, temperature, vibration, and shock. These environmental stresses can cause cracks or other defects in critical components. By using YOLO v8 to detect these defects, automated inspection systems can monitor the performance of materials and identify any structural issues caused by environmental factors. This real-time monitoring helps ensure the safety and reliability of critical infrastructure, reducing the risks associated with undetected cracks or damage.

II. MATERIALS AND METHODS

1. Existing method

Recent research has made significant advancements in the field of crack detection and surface defect identification across various materials using machine learning and deep learning techniques. Dais et al. (2021) utilized convolutional neural networks (CNNs) and transfer learning to automate crack classification and segmentation on masonry surfaces, demonstrating how these methods improve accuracy and efficiency in detecting cracks (1). Similarly, Kang et al. (2021) proposed a hybrid deep learning approach for pixel-level concrete crack segmentation, effectively handling complex backgrounds and environmental noise to enhance crack detection in challenging scenarios (2). Dr. Hansaraj Wankhede (2021) applied CNN-based techniques to detect cracks on rail surfaces, emphasizing the effectiveness of machine learning in automating rail inspections and ensuring the timely identification of potential safety hazards (3). In his earlier work (2020), Wankhede further explored deep learning for crack detection in various materials, highlighting the precision of CNNs in identifying and classifying cracks (4). F.J. Dela Calle (2020) introduced an inspection system for rail surfaces that utilizes differential image techniques, providing a continuous and automated method to detect subtle changes like cracks, thus improving infrastructure monitoring (5). Guo et al. (2016) demonstrated the use of the Kirsch and Canny operators in detecting surface defects in ceramic bowls, successfully identifying small cracks and scratches, showcasing the adaptability of traditional image processing methods for crack detection (7). Yan et al. (2021) employed evolutionary neural networks and computer vision to detect cracks in glass bottles, providing an innovative real-time system that continuously improves its crack detection performance (9). Zheng et al. (2021) introduced a crack defect detection algorithm for MEMS devices, applying advanced image processing and machine learning to detect minute cracks in micro-sized components, highlighting AI's growing role in high-precision fields like electronics (10). Further studies, such as those by Lapusinskij et al. (2021), examined the application of the Hough transform and Canny edge detector methods for visual detection in other domains like meteorology, but the principles could be applied to crack detection as well (11). In the field of energy, Wang et al. (2022) introduced a multi-source information fusion Naive Bayes classification method for generator fault classification, demonstrating how machine learning techniques can be used to diagnose system faults and improve predictive maintenance (12). Zhang et al. (2018) presented a locally attribute weighted Naive Bayes classifier, which could be adapted for defect detection in various materials by enhancing the classification accuracy in imbalanced datasets (13). Bao et al. (2018) proposed a weighted Naive Bayes algorithm optimized with a genetic algorithm, offering a potential approach for improving defect detection in materials that require highly precise classification (14). Wu et al. (2022) explored crop stem recognition and localization using a skeleton extraction algorithm, a technique that can be applied to automate surface defect detection in agricultural materials (15). Finally, Wen and Chen (2021) applied an improved YOLOv4 algorithm for the detection of surface defects in electronic components, showing how advanced deep learning architectures can improve defect detection in complex manufacturing environments (16). These studies collectively highlight the growing integration of AI, deep learning, and image processing technologies in automating defect detection across industries, offering faster, more reliable, and cost-effective solutions for structural health monitoring and quality control.

2. Proposed System

The system is explained through a block diagram, as depicted in Fig. 1, which consists of several key stages. First, the Dataset is collected, containing images of structures with cracks and non-cracks. This dataset is then prepared for further processing. The next step is Labelling, where the images in the dataset are annotated using tools such as Labelling or Rob flow. During this phase, bounding boxes are drawn around the cracks, and the images are labelled accordingly to facilitate training of the YOLOv8 model.

Following this, the YOLOv8 Model is employed. The labelled data is used to train the YOLOv8 (You Only Look Once, version 8) object detection model, enabling it to learn how to identify cracks in the provided images. Once the model is trained, the Model Output is generated, producing a trained detection model capable of detecting cracks in new, unseen images. At the next stage, Input images or a set of images are provided to the trained model for analysis. Finally, during Crack Detection, the trained model processes these input images, identifying cracks and marking their locations or boundaries, producing the final output.

This process allows for efficient, automated detection of cracks in various structural images. The system can be integrated into real-time inspection systems for continuous monitoring and maintenance.

3. Proposed Flow Chart

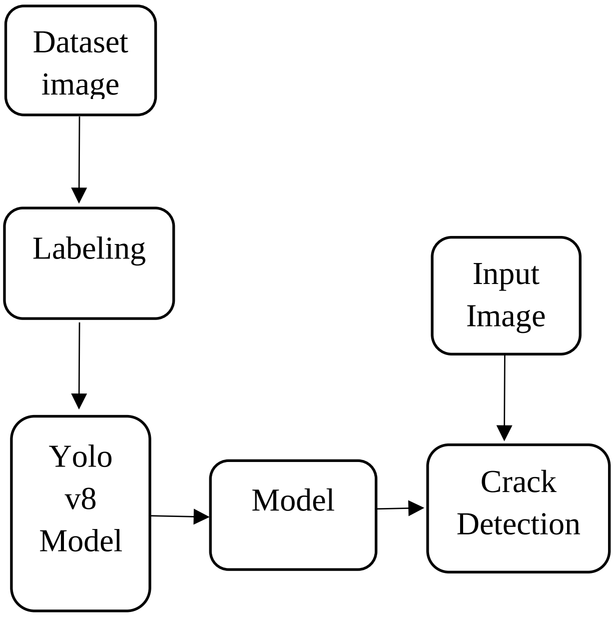

Figure 1.1 Proposed flow chart

III SIMULATION RESULT

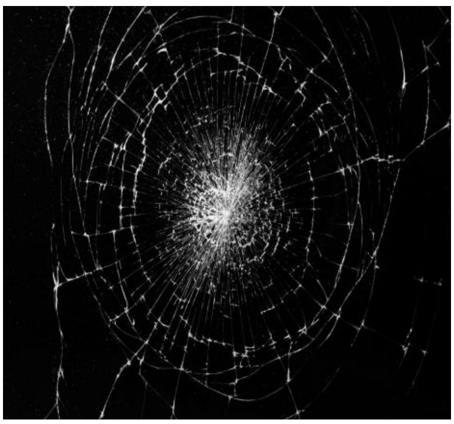

Fig 1.2 INPUT IMAGE

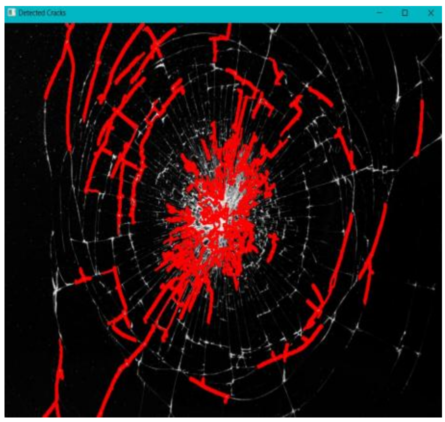

Fig 1.3 OUTOUT IMAGE

Fig 1.4 INPUT IMAGE

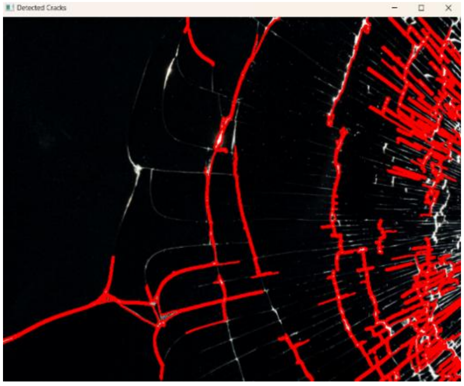

Fig 1.5 OUTPUT IMAGE

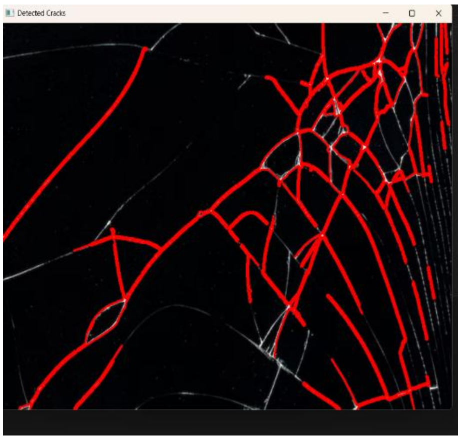

Fig 1.6 INPUT IMAGE

Fig 1.7 OUTPUT IMAGE

Fig 1.8 INPUT IMAGE

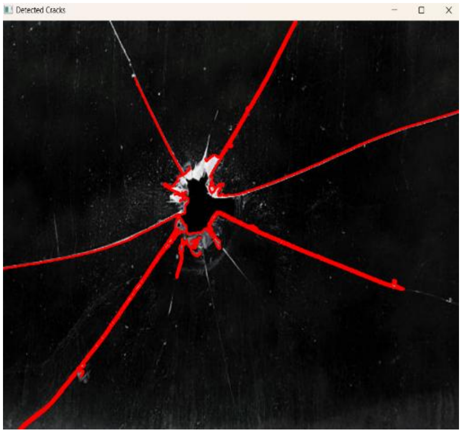

Fig 1.9 OUTPUT IMAGE

IV. Result and Discussion:

The simulation successfully detected cracks in the input image. Figure 1.2 shows the input image of a cracked surface, while Figure 1.3 highlights the detected cracks in red. The output demonstrates that the algorithm accurately identifies the crack patterns, particularly in the central region. However, some noise and minor false positives are observed, suggesting a need for improved preprocessing techniques such as noise reduction and edge enhancement. The method has potential applications in structural health monitoring and material damage assessment. Future work could involve integrating advanced machine learning models to enhance detection accuracy and reliability.

V. CONCLUSION

In conclusion, the detection of cracks in glass and other materials is vital for maintaining their structural integrity and ensuring the safety of products across various industries. Traditional inspection methods, while useful, are often time-consuming and prone to error, highlighting the need for advanced, automated solutions. Technologies like optical imaging, acoustic methods, and thermal analysis offer significant improvements in detecting cracks early, preventing catastrophic failures. The integration of YOLO v8, an advanced object detection algorithm, further enhances crack detection by providing real-time, precise identification of defects in complex environments. This approach not only streamlines inspections but also helps safeguard critical infrastructure in high-stress industries, reducing the risks associated with undetected damage and improving overall reliability and safety.

VI. REFERENCES

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