ENHANCING AUTONOMOUS DRIVING SYSTEMS WITH AI-BASED IMAGE QUALITY ASSESSMENT FOR LENS DEFECT DETECTION

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Abstract. *Autonomous driving systems rely heavily on camera-based perception, making image quality a critical factor in ensuring accurate decision-making. Lens defects, such as dirt, cracks, and scratches, can significantly degrade image quality, leading to poor performance in object detection and navigation tasks. This study presents an AI-based framework for detecting and assessing lens defects in autonomous vehicle cameras. By combining traditional image processing techniques with deep learning models, including a custom-trained YOLOv8, we demonstrate an effective approach to identifying image distortions. Our findings highlight the strengths and limitations of different detection methods and provide insights into improving defect detection in future implementations.*

Keywords*: Autonomous driving, Image Quality Assessment (IQA), Lens defects, Object detection, pre-trained models*

1. Introduction

The effectiveness of autonomous driving systems depends heavily on the quality of the visual data they receive. However, external factors like dirt accumulation, lens scratches, and cracks can degrade image quality, leading to inaccurate detections of objects, lanes, and road signs. This poses a significant challenge for real-world deployment, as impaired perception can compromise safety and reliability.

To address this issue, we explore a multi-faceted approach to detect lens defects using both traditional image processing techniques and modern deep learning models. By comparing methods like thresholding and edge detection with advanced architectures like YOLOv8 and Faster R-CNN, we assess their ability to detect subtle and complex lens distortions. The insights from this study can help develop more resilient autonomous driving systems that adapt to varying environmental conditions.

2. Existing Research and Technologies

Various approaches have been explored to improve image quality in autonomous driving. Traditional methods, such as histogram equalization and contrast stretching, have been used to enhance visibility. More advanced techniques rely on deep learning for defect detection.

Recent advancements in deep learning have introduced sophisticated models for detecting image degradation. Convolutional neural networks (CNNs) and transformer-based architectures have shown significant improvements in defect identification.

Additionally, anomaly detection models like autoencoders have been used to detect image inconsistencies.

Generative Adversarial Networks (GANs) have also been applied in autonomous driving for image enhancement and synthesis under adverse conditions. However, this study focuses on direct defect detection rather than image reconstruction, leaving potential GAN applications for future work.

3. Methods and Models Used

A. Traditional Image Processing

- **Thresholding**: We applied intensity-based thresholding to isolate potential defects.
- **Edge Detection**: We used Canny edge detection to identify scratches and cracks.
- **Morphological Operations**: We applied morphological transformations to refine detections and remove noise.

Results:

- These methods worked well in high-contrast conditions but struggled with subtle defects and noise.
- They also produced a high number of false positives due to background variations.

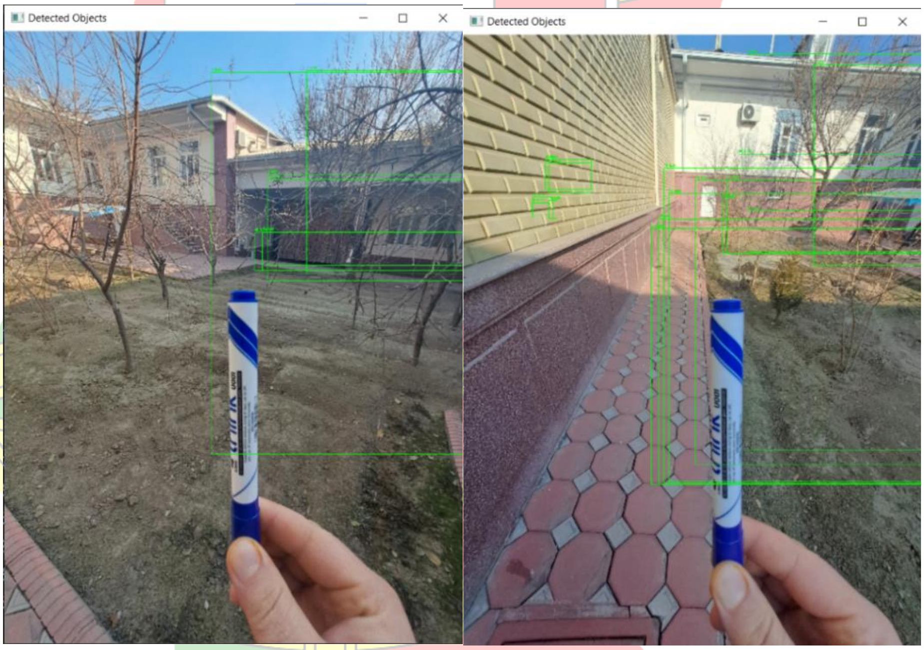

Figure 1: Results of using Torch and Torchvision models to detect objects

B. Pre-Trained Deep Learning Models

- **YOLOv8m**: We used this model for general object detection, but it had difficulty with small, fine-grained defects.
- **Faster R-CNN**: This model provided better feature extraction but was not specifically trained on lens defects, limiting its effectiveness.

Results:

- Both models performed well for large, distinct objects but struggled with minor dirt and scratches.

- Their performance was constrained by the lack of lens defect annotations in the COCO dataset.

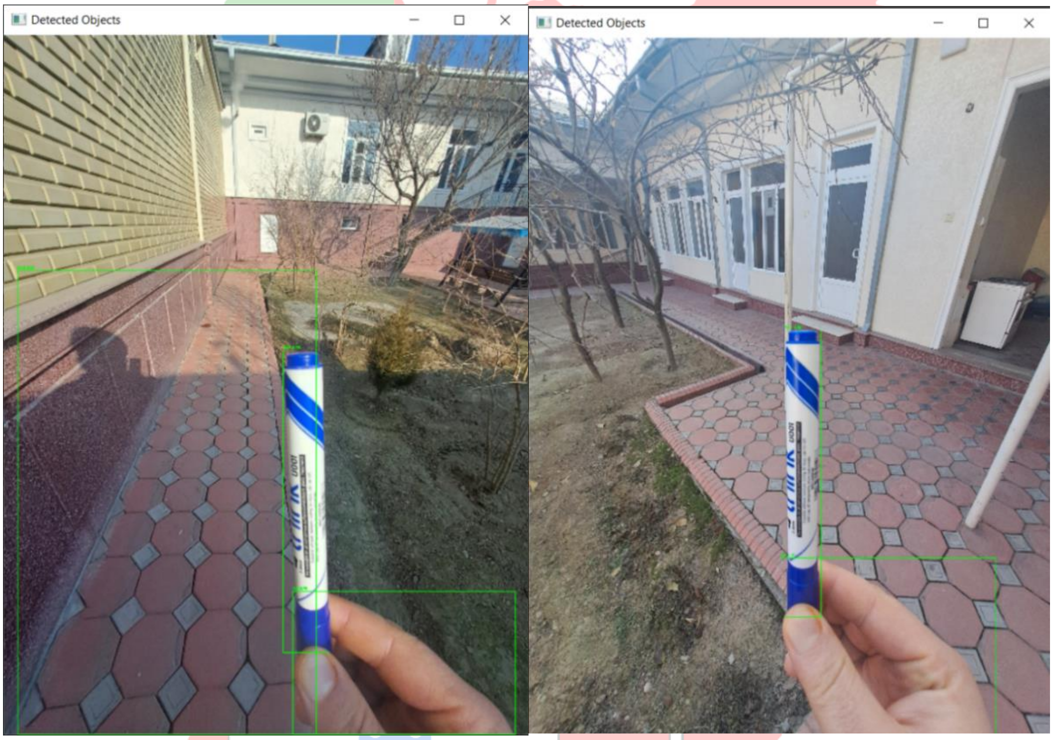

Figure 2: Results of using pre-trained yolo model. It successfully detected the intended item.

Figure 3: Results of using pre-trained yolo model. It failed to detected the intended spot.

C. Custom YOLOv8 and YOLOv9 Models

- **Dataset Creation**: We changed and tested different confidence threshold and annotated a various dataset with various lens defects.
- **Training**: We fine-tuned YOLOv8 and YOLOv9 using the Ultralytics library.

Results:

- The custom model significantly improved object detection compared to pre-trained models.
- However, it still struggled with complex shapes, scratches, single color not standard shaped objects and faint defects, highlighting the need for more diverse training data.

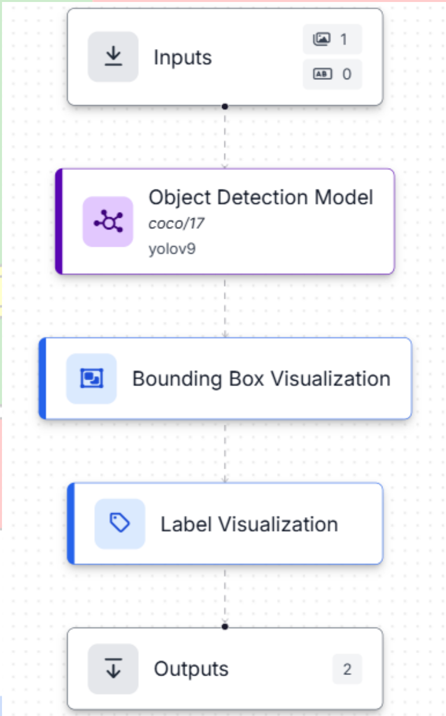

Figure 4: The code algorithm model used in experiments.

4. Proposed System Framework

Our proposed framework consists of multiple stages to enhance image quality and detect lens defects efficiently:

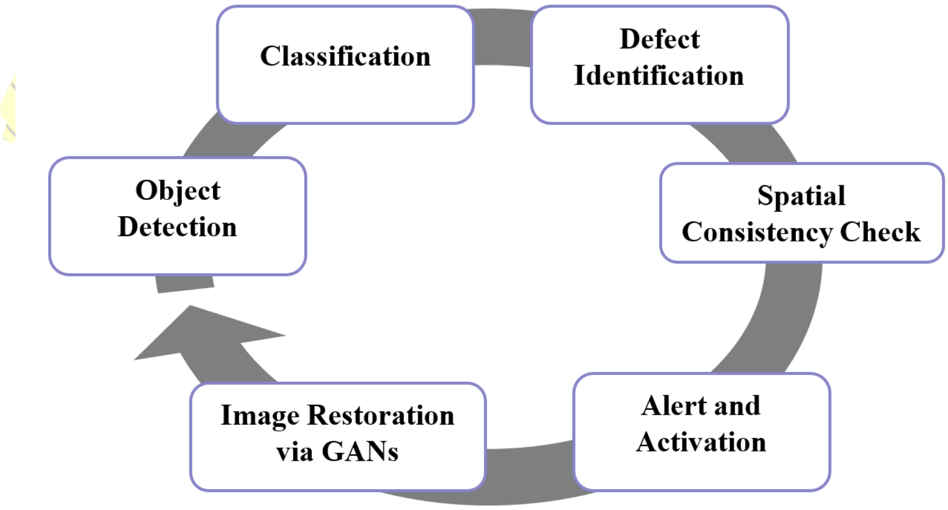

Figure 5: Proposed framework diagram

1) **Object Detection and Classification**:
   - Images captured by the vehicle's camera are processed using YOLO to detect dirt and defects, lanes, obstacles, and traffic signs.

2) **Defect Identification**:

- Anomalies such as scratches and dirt are detected using CNN-based defect identification models.

3) **Sequential Image Analysis**:

- Defects that persist across multiple frames indicate lens-specific issues rather than transient environmental disturbances.

4) **System Alert and Intervention**:

- If defects are detected consistently, the system alerts the user or activates automatic cleaning mechanisms.

5. Experimental Results and Discussion

Using OpenCV visualization tools, we analyzed model outputs by drawing bounding boxes and labels around detected defects. The findings showed that:

- **Traditional methods** were effective for simple cases but produced many false positives.
- **Pre-trained YOLOv8 and Faster R-CNN models** had limited success due to the lack of training on defect-specific datasets.
- **The custom YOLOv8 model** performed better but still required many improvements, especially for fine-grained defect detection.

These results suggest that a dedicated dataset, better annotations, and additional processing techniques (e.g., semantic segmentation) could further enhance performance.

6. Challenges and Limitations

- **Small defect detection**: Hairline cracks and tiny dirt spots remain difficult to detect accurately.
- **Dataset limitations**: Model performance heavily depends on dataset diversity and annotation quality.
- **False positives**: Both traditional and deep learning approaches produced false positives, particularly in cluttered backgrounds.

7. Future Work

To improve detection accuracy, future research will focus on:

- **Expanding the dataset**: Include more varied lighting conditions and environments.
- **Exploring semantic segmentation**: Use models like U-Net or DeepLab to achieve pixel-level defect identification.
- **Investigating anomaly detection**: Use autoencoders or GANs to learn normal image distributions and flag deviations.

8. Conclusion

This study explored various approaches for detecting lens defects in autonomous vehicle cameras. While traditional image processing methods provided basic defect identification, deep learning models like YOLO demonstrated greater potential, particularly when fine-tuned with a dedicated dataset. However, challenges remain in detecting subtle defects, necessitating further dataset improvements and advanced segmentation techniques. Enhancing defect detection capabilities will contribute to safer and more reliable autonomous driving systems.

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