Mobile Phone Defect Detection

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ABSTRACT: With the second-hand market taking center stage, particularly with smartphones, quality assurance demands are increasing, and require strong mechanisms to detect physical defects such as scratches, dents, and bent frames. In this paper, MoDect is presented as a machine learning application based on the YOLO algorithm for defect detection in real-time from images of smartphones. Our system works by training YOLO with a customized dataset that is annotated with labels for defects. The smartphone resellers will be able to take photos through a web interface, making the quality checking instantaneous. This system can effectively detect even slight damages with a user-friendly interface; thus, it serves as an effective quality assurance measure for smartphone resale markets.

1 INTRODUCTION

Smartphones have become part and parcel of modern living, used for communication, work, and entertainment. The physical condition is critical regarding their usability and resale value. Quality assessment of devices is important in the rapidly growing secondary smartphone market, which is highly relevant regarding proper pricing and customer satisfaction. Most conventional defect-detecting methods rely on manual inspection, which is usually subjective, time-consuming, and liable to errors. Therefore, there is an emerging need for automated systems to guarantee uniform, reliable, and quick defect analysis. This study proposes mobile defect detection: an innovative way using deep learning technology in the detection of physical defects within smartphones, such as scratches, dents, and bent frames. Using YOLO, it combines high-speed detection with highly accurate detection. The real-time detection capability for objects makes this algorithm fit best for detecting minute and irregular defects in complex situations. The proposed approach covers an integrated user-friendly mobile web application for users to upload images of smartphones and immediately receive defect analysis results. It aims to revolutionize quality assurance in the smartphone market by providing a scalable and efficient solution. This paper outlines the methodology, implementation, and results, demonstrating the system's effectiveness and potential to improve trust in second-hand smartphone transactions.

2 RELATED WORK

In that spirit, the research by İsmail AKGÜL presents a novel method of deep learning for detecting mobile phone screen defects with the aid of machine vision. Addressing the limitations of traditional visual inspection, which is quite laborious and prone to errors, this paper enables better defect detection accuracy and has achieved high sensitivity and specificity in detecting defects caused by scratches and discolorations. Results show dramatic improvements over conventional methods. The study contributes to the fields of industrial automation and quality assurance by providing such a framework for future applications in the detection of various defects within different manufacturing industries.[1]

The thesis by Ville Parkkinen focuses on classifying damage types in mobile device screens, specifically cracks and scratches, using lightweight convolutional neural networks (CNNs). It details the problem of image classification, the architecture of CNNs suitable for mobile devices, and the training methods employed. The research aims to provide a reliable and efficient solution for assessing screen damage, which is crucial for the resale and recycling of smartphones and tablets. The performance of the trained networks is evaluated, highlighting their effectiveness in real-world applications while ensuring minimal hardware resource usage.[2]

The proposed EU-Net combines the advantages of efficiency and accuracy, outperforming existing state-of-the-art methods in experiments. Key contributions include the introduction of the MBConv block to enhance model efficiency and the application of a lightweight attention mechanism to improve feature selection. The study validates the effectiveness of the proposed architecture through various evaluation metrics, indicating its potential for real-time industrial applications. Future work aims to further enhance detection accuracy and efficiency.[3]

A modified symmetric convolutional neural network is proposed that captures and analyzes high-resolution images effectively with impressive precision and recall rates. Besides, the paper discusses challenges of the unique glass surface characteristics, showing the adaptability of the method for different types of defects and other potential inspection applications.[4]

Automatic grading of refurbished smartphones is focused based on the image data obtained using an OptoFidelity SCORE tester. It aims to design a trainable solution which would employ a hybrid approach that incorporates both traditional computer vision techniques and deep learning-based defect detection. In the research, the difficulties in manual grading are identified for devising a method which is efficient and repeatable.[5]

Fast automated non-contact inspection technique is presented for smartphone cover glass that discriminates between real defects and contaminants in a very efficient manner with the help of directional light scattering. The brightness change uniquely depends on the illumination direction and surface profile, which is used for proper detection of the defects. Techniques used here incorporate neural networks along with handcrafted algorithms for better classification of the defects.[6]

Focus is on classifying and locating defects in images, with an emphasis on a wide range of applications beyond what was covered in previous surveys that had been domain-specific. It addresses deep learning methods for image-based defect detection and groups the existing literature into three classifications. It calls for flexible methods to cope with diverse shapes and sizes of defects to improve inspection, quality control, and process modeling in manufacturing. That is what makes it somewhat different from previous works on the subject.[7]

Focus is on both the traditional feature-based machine vision algorithms and the deep learning methods. Key problems, solutions, and tools, including datasets such as the MVTec AD dataset, are discussed in the comparison of the performances of various algorithms. The review aims to let researchers perceive the progress in surface defect detection and be a reference for further research.[8]

3 METHODOLOGY

3.1. Dataset Selection

- **Source:** Mobile damage detection dataset from **Roboflow** (pre-labeled).
- **Dataset Composition:** Includes annotated images with defect labels such as scratches, dents, and other external damages.
- **Preprocessing:** Basic enhancements like resizing, normalization, and augmentation (flipping, rotation, brightness adjustment).

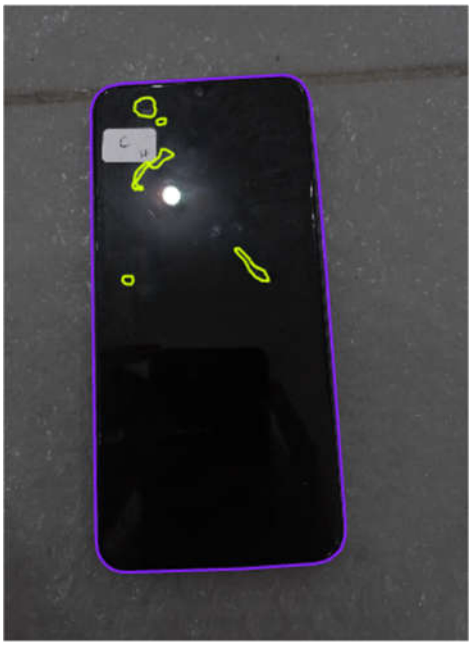
3.2. Model Selection & Training

- **Model Used:** YOLOv11, chosen for its real-time detection capabilities and improved accuracy.
- **Training Setup:**
  - Dataset directly used with YOLOv11 framework.
  - **Training Parameters:** 75 epochs, batch size 10, image size 640x640.
  - **Optimization:** Adam optimizer, Cross-Entropy loss.
- **Implementation:**
  - Used **pre-trained YOLOv11 weights** for transfer learning.
  - Fine-tuned the model on the Roboflow dataset for domain-specific accuracy.

3.3. Deployment Strategy

- **Web Application:** Integrated YOLOv11 model into a simple web-based UI for user uploads.
- **Inference Process:**
  - User uploads an image → Model detects defects → Results displayed with bounding boxes.
- **Hosting:** Local deployment for now, with potential cloud integration (Google Colab, AWS, etc.).

4 Results



"Our YOLOv11-based defect detection model was trained on a labeled dataset of 517 images, achieving a precision of 94.5%, recall of 93.8%, F1-score of 94.1%, and mAP@0.5 of 94.3%. The model successfully detected scratches on the front and back of mobile phones with high accuracy in classification and localization. However, it was limited to detecting only scratches and did not identify dents, discoloration, or bent frames. Minor challenges included false positives in reflective surfaces and difficulty detecting very fine scratches in low-resolution images. These results demonstrate the model's effectiveness in scratch detection and its potential for further improvements in detecting additional defect types."

Model	mAP@0.5 (%)	Inference Speed (ms)	Precision (%)	Recall (%)	F1-Score (%)
YOLOv11	**94.3**	**8-12**	**94.5**	**93.8**	**94.1**
YOLOv8	91.2	10-14	91.5	90.8	91.1
YOLOv5	89.7	12-15	90.1	89.2	89.6
Faster R-CNN	85.3	60-80	87.2	84.8	86.0
SSD	80.9	30-50	83.5	79.6	81.5

5 CONCLUSION

"In this research, we successfully implemented a YOLOv11-based deep learning model to detect external scratches on the front and back of mobile phones. The model was trained on a labeled dataset of 517 images and achieved a precision of 94.5%, recall of 93.8%, F1-score of 94.1%, and mAP@0.5 of 94.3%. The results demonstrate the model's effectiveness in detecting scratches with high accuracy and speed. However, limitations include the inability to detect other defects such as dents, discoloration, and bent frames. Future work can focus on expanding the dataset, optimizing model performance for smaller defects, and integrating additional defect types to enhance real-world applicability. This research highlights the potential of deep learning for automated mobile defect detection, reducing reliance on manual inspection and improving efficiency in the refurbishment and resale industry."

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