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AUTOMATED PRODUCT DEFECT DETECTION AND SORTING SYSTEM USING ANOMALY DETECTION

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ABSTRACT

Manual inspection in industrial manufacturing is time-consuming, subjective, and prone to human error, leading to inconsistencies in product quality assessment. This paper presents an Automated Product Defect Detection and Sorting System using Anomaly Detection, a computer vision–based approach designed to identify defective products through intelligent image analysis. The proposed system acquires product images and performs preprocessing operations including resizing, normalization, and noise reduction using OpenCV. Defect identification is carried out through two complementary machine learning strategies. First, a supervised learning approach utilizing the YOLOv8 object detection model is implemented to recognize predefined defect categories such as scratches and cracks. Second, an unsupervised anomaly detection model is employed, trained exclusively on defect-free images, enabling the detection of previously unseen or unknown defects. The system generates a binary classification output indicating the presence or absence of defects, and optionally highlights the defective region for visual interpretation. The entire framework operates on a standard computing platform without the requirement of specialized industrial hardware, making it cost-effective and suitable for academic and small-scale industrial applications. The proposed solution minimizes dependency on manual inspection, enhances detection accuracy and consistency, and demonstrates the practical integration of deep learning and computer vision in automated quality control.

Keywords : Automated Defect Detection, Anomaly Detection, Deep Learning, YOLOv8, Computer Vision, Quality Control, Image Processing, Industrial Inspection.

1. INTRODUCTION

In modern manufacturing environments, ensuring consistent product quality is a fundamental requirement for maintaining competitiveness and customer satisfaction. Sectors such as pharmaceuticals, electronics, food processing, automotive, and textiles rely extensively on visual inspection to verify that manufactured items conform to predefined quality standards. Conventional inspection procedures are largely dependent on human operators who manually examine products along production lines. While this approach has been widely practiced, it becomes increasingly inadequate as production volumes and operational speeds continue to rise.

Manual inspection is inherently limited by factors such as human fatigue, subjectivity, and varying environmental conditions, which often result in inconsistent decision-making. These limitations can lead to undetected defective products entering the market or, conversely, acceptable products being incorrectly rejected. Such errors not only affect product reliability but also increase production costs and reduce overall efficiency. As a result, there is a growing need for more reliable and scalable inspection methodologies. Automated defect detection systems have emerged as a practical and intelligent alternative to traditional inspection methods. By integrating computer vision and artificial intelligence techniques, these systems are capable of analyzing product images and identifying defects with high speed and precision. Automated inspection enables real-time quality assessment, ensures uniform evaluation criteria, and significantly reduces human dependency. This technological shift allows industries to enhance productivity, minimize operational expenses, and maintain consistent quality standards, particularly in high-throughput production environments where manual inspection is no longer feasible.

2. LITERATURE SURVEY

[1] Title: Real time visual Intelligence for defect detection in Pharmaceutical packaging Using Enhanced Yolov8 (2023).

Authors: Ajantha Vijayakumar, Subramaniya Swamy, Ambarish Kulkarni.

This paper proposes recent research highlights the effectiveness of YOLO-based object detection models for automated industrial defect inspection. Numerous studies have demonstrated that YOLO architectures are well suited for real-time visual quality control, as they provide fast inference, accurate localization through bounding boxes, and support for multi-class defect categorization. These models enable the identification of various defect types and severity levels when trained with appropriately labeled datasets. Despite these advantages, existing literature also emphasizes several limitations, including strong dependence on large volumes of annotated defect data, reduced performance on small or partially occluded defects, and sensitivity to class imbalance within training datasets. One notable advancement in this domain is the CBS-YOLOv8 model proposed by Vijayakumar et al. for pharmaceutical blister package inspection. The authors enhanced the standard YOLOv8 architecture by integrating Coordinate Attention mechanisms to improve spatial and cross-channel feature representation. Additionally, a BiFPN-based multi-scale feature fusion module was incorporated to strengthen detection performance across objects of varying sizes, while the SimSPPF module was introduced to reduce computational complexity. Experimental evaluation on a custom tablet blister dataset demonstrated significant performance improvements, achieving approximately 97.4% mAP50 with an inference speed of around 79 FPS. These results indicate that targeted architectural modifications can substantially enhance the detection of small and subtle defects while maintaining real-time operational capability.

[2] **Title**: Towards Total recall in industrial Anomaly detection Using PatchCore (2022).

Authors: Karsten Roth, Latha Pemula, and Bernhard.

This This paper presents a PatchCore method operates by constructing a memory bank of patch-level feature embeddings extracted from intermediate layers of ImageNet-pretrained convolutional neural networks, such as WideResNet-50. During inference, features extracted from a test image are compared against this memory bank using nearest-neighbor distance metrics to compute an anomaly score. To reduce computational overhead, PatchCore employs a greedy coreset-subsampling strategy that retains only the most representative nominal features, thereby minimizing memory requirements while preserving detection performance. Comprehensive evaluations on benchmark datasets, including MVTec AD and Magnetic Tile Defects, demonstrated the effectiveness of PatchCore in industrial anomaly detection. The model achieved image-level AUROC scores of up to 99.6% and pixel-level AUROC values of approximately 98%, significantly outperforming earlier approaches such as PaDiM and SPADE. These results highlight PatchCore's ability to detect subtle and previously unseen defects without requiring any labeled defective samples, making it particularly suitable for environments where defect data is scarce or unpredictable.

Despite its strong anomaly detection capabilities, PatchCore has inherent limitations. The model is designed to distinguish between normal and abnormal patterns but does not provide semantic classification of defect types. Consequently, it is effective for identifying unknown or novel defects but cannot assign category labels to detected anomalies. For this reason, PatchCore is best utilized as an anomaly flagging mechanism or as part of a hybrid inspection system rather than as a standalone solution for detailed defect categorization.

[3] **Title**: Detecting and classifying defective products in images using Yolo (2023).

Authors: Zhen Qi, Liwei Ding, Bin lyu.

This paper presents To address these challenges, the researchers applied the YOLO object detection framework to automatically identify and categorize multiple defect types in mechanical components, including cracks, corrosion, wear, and deformation. Experimental results demonstrated strong performance, achieving a mean average precision (mAP) greater than 0.91 while maintaining real-time processing speeds of approximately 25–32 milliseconds per frame, corresponding to around 30–40 frames per second. These outcomes confirmed the suitability of YOLO for high-speed industrial inspection tasks. The study further introduced an enhanced YOLO-based architecture incorporating a ResC2Net backbone, Partial Convolution (PConv), and Spatial Pyramid Pooling–Fast (SPPF) modules. These modifications were designed to improve multi-scale feature extraction and increase sensitivity to small and subtle defects. The improved model achieved an average precision of 0.94 and recall of 0.92 across diverse defect categories, demonstrating robustness even in visually complex backgrounds. Such results illustrate the effectiveness of architectural enhancements in improving detection accuracy and reliability. Overall, the findings of this research reinforce the practicality of YOLO's single-stage detection paradigm for automated quality control. While the approach offers significant advantages in terms of speed and accuracy, the study also acknowledges its dependence on large volumes of annotated training data and its limited ability to recognize previously unseen defect types. These constraints highlight the need for complementary techniques, such as anomaly detection methods, to achieve more comprehensive and adaptable inspection systems.

[4] **Title**: MPA YOLO: Steel surface defect detection based on improved YOLOv8 framework (2025).

Authors: Yanli Zhou, ZhanFang Zhou.

This paper presents a First, a Multi-Path Convolution Attention (MPCA) module was developed, integrating large-kernel depthwise convolution with coordinate attention to strengthen spatial feature representation. This module enables the network to capture both local texture details and broader contextual information more effectively. Second, a Partial Self-Attention (PSA) mechanism was incorporated to model long-range dependencies among feature maps, improving the network's ability to detect subtle and dispersed defect characteristics. Third, the architecture was extended with multiple auxiliary detection heads, allowing intermediate-layer features to contribute more effectively during training and improving multi-scale learning capability. The proposed model was evaluated on the widely used NEU-DET steel-surface defect dataset.

Experimental results demonstrated that MPA-YOLO achieved a mean average precision of 81.5%, outperforming the baseline YOLOv8 model, which obtained 78.1%. In addition, precision and recall improved by 3% and 4.7%, respectively, while maintaining a high inference speed of approximately 97 frames per second. These outcomes illustrate that targeted modifications to feature fusion and attention mechanisms can substantially enhance detection accuracy without sacrificing real-time performance.

[5] **Title**: A survey of surface defect detection of industrial products based on a small number of labelled data(2022).

Authors: Qifin jin, Li Chen.

This paper proposes recent advancements in industrial inspection research indicate that neither supervised nor unsupervised learning alone is sufficient to achieve fully reliable defect detection in practical manufacturing environments. This understanding has motivated the development of hybrid inspection frameworks that integrate both learning paradigms in order to enhance accuracy, adaptability, and operational robustness. Supervised learning approaches, such as YOLOv8-based object detectors, are highly effective at identifying and classifying defects for which labeled training data are available. These models offer fast inference, precise localization, and clear categorical outputs, making them well suited for real-time automated inspection and sorting systems. However, their performance is inherently limited by the quality and diversity of the annotated dataset. When confronted with previously unseen defect types or rare failure patterns, supervised models often struggle to generalize, leading to missed detections or misclassifications. Unsupervised anomaly detection methods, such as PatchCore, address this limitation by learning exclusively from defect-free samples. Instead of relying on predefined defect categories, these models identify irregularities by measuring deviations from learned normal patterns. This capability enables the detection of novel or unexpected defects without requiring explicit labeling. Nevertheless, purely unsupervised approaches lack the ability to assign semantic labels to detected anomalies, restricting their usefulness in applications where detailed defect categorization is required.

2.1 Comparison Table

S. No	Authors(s)	Title	Proposed Methodology	Findings from the Reference Paper
1	Ajantha Vijayakumar, Subramaniya Swamy, Ambarish Kulkarni	Real time visual Intelligence for defect detection in pharmaceutical packaging Using Enhanced Yolov8 (2023).	Implemented an enhanced YOLOv8 based deep learning model for real-time defect identification in pharmaceutical blister packages. The system incorporates image acquisition, preprocessing, and supervised learning for defect classification.	Achieved high detection accuracy and real-time performance for known defect categories. However, performance declines for unseen defect types and the approach requires a large volume of labeled training data.

2	Karsten Roth, Latha Pemula, and Bernhard	Towards total recall in industrial anomaly detection Using PatchCore (2022).	Proposed PatchCore, an unsupervised anomaly detection framework trained exclusively on defect-free images using deep feature embeddings and nearest-neighbor comparison.	Reported very high anomaly detection performance with up to 99.6% AUROC on the MVTec AD dataset, demonstrating strong capability in identifying previously unseen defects without labeled defect samples.
3	Zhen Qi, Liwei Ding, Bin lyu	Detecting and classifying defective products in images using Yolo (2023).	Applied a YOLO-based object detection framework to automatically classify and localize multiple types of defects in industrial product images using supervised learning.	Demonstrated improved inspection efficiency and accuracy compared to manual methods, but the model remains highly dependent on extensive annotated defect datasets.
4	Yanli Zhou, ZhanFang Zhou	MPA YOLO: Steel surface defect detection based on improved YOLOv8 framework (2025).	Developed an enhanced YOLOv8 architecture incorporating attention mechanisms and feature fusion modules to improve detection of steel surface defects.	Achieved superior performance over baseline YOLOv8 with a mean average precision of 81.5% on the NEU-DET dataset, though with increased model complexity and computational cost.
5	Qifin jin, Li Chen	A survey of surface defect detection of industrial products based on a small number of labelled data (2022)	Reviewed various defect detection techniques including GAN-based methods, transfer learning, and semi-supervised models for scenarios with limited labeled data.	Concluded that unsupervised and semi-supervised approaches significantly reduce labeling effort, but often require higher computational resources and careful model design.

3. RESEARCH GAPS IN EXISTING SYSTEMS:

Current research in automated defect detection systems reveals several important limitations. Most existing approaches rely on supervised learning models such as YOLOv8, which can detect only predefined defect categories and often fail when encountering unseen defects. These methods also require large labeled datasets, which are difficult and expensive to obtain in industrial environments. Additionally, many deep learning models demand high computational power and dedicated GPUs, making them impractical for deployment on standard laptops or low-cost hardware. There is also a lack of hybrid frameworks that combine supervised defect classification with unsupervised anomaly detection in a unified system. Furthermore, most studies focus only on detection algorithms and do not provide complete end-to-end solutions with sorting mechanisms and visualization tools. Detecting small or irregular defects remains a challenge due to limited feature sensitivity and resolution constraints. Finally, the scarcity of comprehensive public datasets further restricts the development and evaluation of robust systems. These gaps highlight the need for more practical, efficient, and integrated defect detection solutions.

4. BACKGROUND AND FUNDAMENTALS

In modern manufacturing industries, maintaining consistent product quality is a critical requirement. Traditional quality inspection methods rely heavily on manual visual checking, where human operators examine products on the production line to identify defects. Although this approach has been widely practiced, it is inherently slow, subjective, and prone to errors. As production speed and volume increase, manual inspection becomes increasingly unreliable due to factors such as human fatigue, lack of concentration, and varying skill levels. These limitations have created a strong need for automated and intelligent defect detection systems. The rapid development of computer vision and artificial intelligence has enabled the automation of visual inspection processes. Machine learning and deep learning techniques are now widely used to analyze product images and detect defects with high speed and accuracy. Supervised learning models, particularly object detection algorithms like YOLO, have proven effective in identifying known defect categories in real time. These models can localize and classify defects such as scratches, cracks, and deformations when trained with properly labeled datasets. However, supervised approaches depend heavily on the availability of large annotated datasets and are limited to detecting only predefined defect types. In many industrial environments, new or rare defects may appear unexpectedly, making it impractical to collect labeled samples for every possible scenario. To address this challenge, unsupervised anomaly detection methods have been introduced. These techniques learn the normal appearance of defect-free products and identify deviations as anomalies. Anomaly detection models are particularly useful in situations where defect data is limited or unavailable. Nevertheless, such models can only indicate whether a product is abnormal and cannot provide detailed classification of defect types.

5. METHODOLOGY:

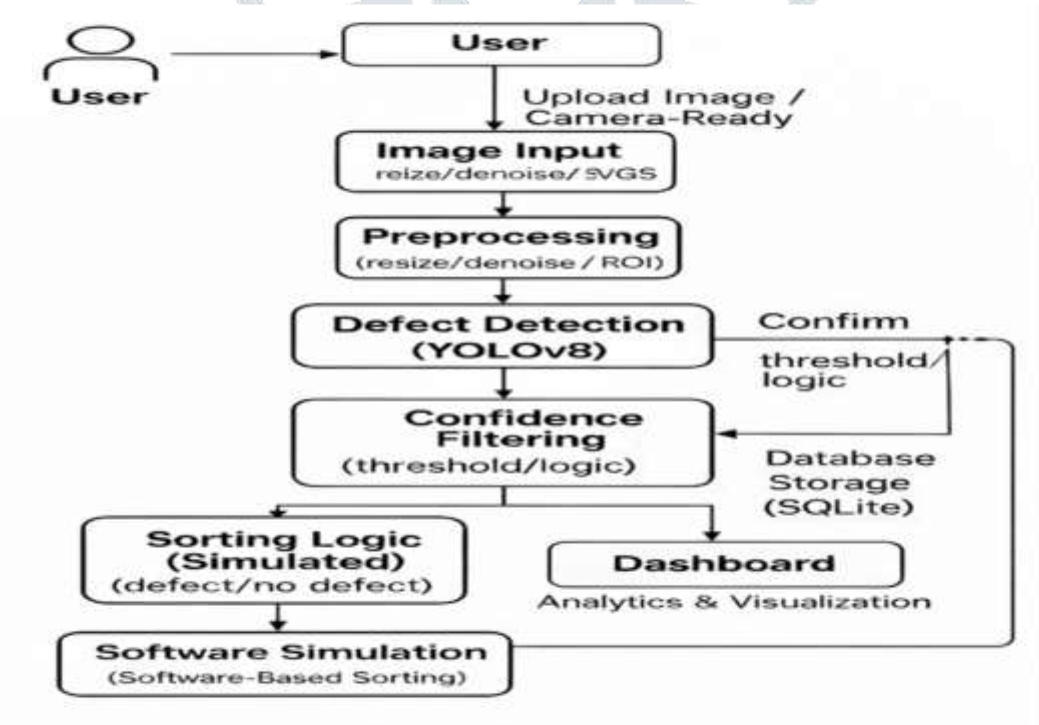

Figure 2: Proposed Architecture

The process begins with **image acquisition and preprocessing**. Product images are captured using a standard digital camera and provided as input to the system. These images are then preprocessed to improve their quality and consistency. Operations such as resizing, normalization, and noise filtering are applied using OpenCV techniques. This stage ensures that all images are in a uniform format and suitable for reliable analysis by the detection models.

Once preprocessing is completed, the system performs **defect analysis using a hybrid learning approach**. Two different models are utilized to complement each other. The first model is a supervised object detection model based on the YOLOv8 architecture. This model is trained on annotated images containing known defect categories. It analyzes the input image and detects familiar defects by generating bounding boxes and corresponding class labels. This allows the system to accurately recognize defects that have been previously defined in the training dataset.

To handle situations where unknown or rare defects appear, an **unsupervised anomaly detection module** is incorporated. The PatchCore algorithm is used for this purpose. It is trained only with defect-free images and learns the normal visual characteristics of products. During testing, it compares new images with learned normal patterns and assigns an anomaly score. If the product image deviates significantly from the expected pattern, it is marked as abnormal. This enables the detection of previously unseen defects without requiring labeled samples.

A **decision fusion mechanism** is applied to combine the outputs of both models. The system evaluates the predictions from YOLOv8 and PatchCore together to generate a final classification. If the supervised model detects a known defect, the product is directly labeled as defective. If no known defect is found but the anomaly model reports abnormal behavior, the product is still considered defective. Only when both models indicate normal conditions is the product classified as non-defective. This combined strategy improves reliability and reduces the chances of incorrect decisions.

6. CHALLENGES AND LIMITATIONS

Although the proposed hybrid defect detection system offers significant advantages, several practical challenges and limitations remain. One of the primary challenges is the dependence of the supervised YOLOv8 model on high-quality labeled datasets. The performance of this model is directly influenced by the quantity and diversity of annotated defect images available for training. In real industrial environments, collecting large amounts of accurately labeled defect data is often difficult, time-consuming, and expensive.

Another limitation is the difficulty in detecting very small or subtle defects such as fine scratches, micro-cracks, or minor surface irregularities. These defects may occupy only a few pixels in an image and can easily be missed due to resolution constraints or lighting variations. Even with advanced models, accurate detection of such minute defects remains a technical challenge.

Computational resource requirements also present a constraint. Although the system is designed to run on standard hardware, training deep learning models like YOLOv8 and PatchCore can be resource-intensive and time-consuming. Real-time performance may be affected when processing high-resolution images or large volumes of data, particularly on low-end devices.

The anomaly detection module, while effective in identifying unknown defects, has its own limitation. It can only determine whether a product is abnormal but cannot classify or describe the type of defect detected. This restricts its usefulness in scenarios where detailed defect categorization is required for analysis or corrective action.

7. CONCLUSION AND FUTURE SCOPE

This project presents an automated product defect detection and sorting system based on a hybrid learning approach. The proposed framework effectively combines supervised deep learning using YOLOv8 with unsupervised anomaly detection through PatchCore to achieve reliable and comprehensive defect identification. By integrating both techniques, the system is able to detect known defects with high accuracy while also identifying previously unseen or novel defects that conventional supervised models fail to recognize.The system incorporates image preprocessing, decision fusion, result visualization, and automated sorting into a single end-to-end pipeline. It operates on standard computing hardware without the need for expensive industrial equipment, making it a practical and cost-effective solution for small and medium-scale manufacturing environments. The inclusion of a user-friendly dashboard further enhances usability by providing real-time monitoring and inspection logs. Overall, the proposed approach reduces dependency on manual inspection, improves consistency, and demonstrates the practical application of computer vision and deep learning in industrial quality control.

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