Research and Design of an Automated Tray-based MOSFET Pin Fault Inspection System using YOLOv8 Deep Learning Model

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Abstract

This paper presents the development of an automated inspection system for detecting defects in MOSFET components arranged on tray matrices using computer vision and deep learning. The proposed system integrates an X–Y motion platform, an industrial camera, and a lightweight object detection model based on YOLOv8n to perform real-time inspection. The model is trained to classify two classes: MOSFET and Empty, enabling accurate localization of components on a 12×12 tray with up to 144 positions. After detection, image processing techniques including grayscale conversion, threshold segmentation, and contour analysis are applied to evaluate the geometric condition of MOSFET leads and detect defects such as bent or missing pins. Experimental results show that the trained model achieves high performance with Precision of 0.997, Recall of 1.0, and mAP@0.5 of 0.995. The developed human–machine interface (HMI) provides real-time visualization of inspection results and tray status. The proposed system demonstrates reliable performance and provides an effective solution for automated quality inspection in electronic component manufacturing.

Keywords

MOSFET component inspection, automated defect inspection, industrial image processing, YOLOv8, machine vision.

Abbreviations

Symbol	Description
ROI	Region of Interest in the image
mAP@0.5	Mean Average Precision at IoU threshold of 0.5
Epoch	One complete training iteration of the model over the dataset
Batch size	Number of image samples used in one weight update
Imgsz	Input image size of the model
AI	Artificial Intelligence
CNN	Convolutional Neural Network
HMI	Human Machine Interface
PCB	Printed Circuit Board
ROI	Region of Interest
UART	Universal Asynchronous Receiver Transmitter
YOLO	You Only Look Once
mAP	Mean Average Precision

1. Introduction

In the context of the rapid development of the electronics industry and the increasing trend toward automation in manufacturing, ensuring the quality of semiconductor components before they enter the assembly line plays a crucial role in improving product reliability. Power semiconductor devices such as MOSFETs are widely used in switching power supplies, inverters, and electronic control systems. Therefore, physical defects in the component leads—such as bent, broken, or missing pins—may cause serious problems during the soldering process on printed circuit boards (PCBs), leading to equipment failure or reduced lifetime of electronic systems.

In practical manufacturing environments, the inspection of electronic components prior to assembly is still mainly based on manual or semi-automatic methods. These approaches rely heavily on the experience of operators and are prone to errors when production volume is large or when defects are very small. To address this issue, many studies have focused on applying computer vision and deep learning techniques to automate the component quality inspection process.

In semiconductor manufacturing, Automated Optical Inspection (AOI) systems have been widely deployed to detect surface defects and structural inconsistencies of components. Traditional AOI systems rely on rule-based image processing techniques, which often struggle with variations in lighting conditions, component positioning, and complex defect patterns. Recent advancements have introduced deep learning-based AOI approaches that significantly improve robustness and adaptability by learning discriminative features directly from data.

Several studies have applied deep learning to classification and defect detection problems in industrial manufacturing. For instance, the authors in [1] proposed a deep learning model based on the TensorFlow platform to classify defective products in the production of components for electric vehicles. The results demonstrated that deep learning methods can effectively analyze image features and classify products as qualified or defective with high accuracy, thereby improving the efficiency of automated inspection processes in industrial manufacturing.

In addition, recent studies have focused on developing object detection models based on the YOLO architecture to enhance the performance of automated inspection systems. Ong et al. proposed the SEConv-YOLO model to improve defect detection on PCB and PCBA boards. This approach employs squeeze–excitation convolution modules combined with a weighted spatial pyramid pooling structure to enhance feature extraction capability and improve defect detection accuracy in industrial environments [2].

For lightweight and real-time industrial inspection tasks, model efficiency and detection accuracy for small-scale features are critical factors. Compared with other lightweight detectors such as YOLOv10-N or NanoDet, YOLOv8n provides a favorable balance between computational cost and detection performance, particularly due to its improved feature fusion mechanism and anchor-free design, which enhances its ability to detect fine-grained objects such as component leads. This makes it a suitable candidate for deployment in high-speed production environments with limited computational resources.

Existing studies on object detection in industrial environments mainly focus on general defect detection; however, limited attention has been given to the specific challenge of detecting fine lead defects in densely arranged semiconductor components on trays. These scenarios require not only accurate localization but also precise geometric analysis to identify subtle defects such as slight bending or missing pins.

Beyond electronics manufacturing, image processing and machine learning techniques have also been widely applied in various intelligent robotic and automation systems. In [3], image processing techniques were used to support a robotic cane that assists visually impaired individuals in maintaining balance and navigating along guided paths, demonstrating the potential of computer vision in assistive robotic applications. Similarly, machine learning and computer vision models have been applied to recognize traffic light signals and provide warning assistance for intelligent transportation systems, thereby improving road safety and supporting autonomous driving technologies [5]. In addition, Lam et al. proposed a real-time multi-object recognition and classification framework for automated robots operating on resource-constrained devices [7]. Their study demonstrated that lightweight deep learning models can achieve efficient object detection and classification performance while maintaining real-time processing capability on embedded robotic platforms. This work highlights the feasibility of deploying computer vision algorithms in practical robotic systems with limited computational resources and further supports the applicability of lightweight YOLO-based approaches for industrial automation tasks.

For object detection tasks in complex environments, many studies have improved the YOLO architecture to enhance performance and adaptability under real-world conditions. Liu et al. proposed the RFEA-YOLO model for detecting faults on power transmission lines under adverse weather conditions such as rain and fog by integrating attention mechanisms and adaptive receptive fields [4]. Similarly, Tian et al. developed the YOLOv8n-EdgePro model for insulator detection in power distribution networks. This lightweight architecture is suitable for edge devices and real-time applications [6].

Despite these advancements, applying deep learning to MOSFET lead inspection on trays still presents challenges related to small object size, dense arrangement, and the requirement for high-speed processing. Moreover, purely deep learning-based approaches may not fully capture geometric irregularities of leads, which are critical for defect identification.

Although these studies have demonstrated the effectiveness of deep learning and computer vision methods across various domains, applying these techniques to the problem of detecting defects in semiconductor component leads arranged on trays still presents several challenges. The components are typically small, densely arranged on trays, and require the inspection system to operate at high speed to meet the demands of production lines.

Motivated by these practical requirements, this paper focuses on the research and design of an automated inspection system for detecting MOSFET lead defects on trays based on computer vision and deep learning technologies. The main contribution of this work lies in a hybrid inspection approach that combines YOLOv8n-based object detection with geometric contour analysis to improve defect identification accuracy for fine lead structures. In addition, the study presents an integrated mechatronic system consisting of a high-precision X–Y motion mechanism, an industrial camera for image acquisition, and a centralized control software system, enabling synchronized inspection and real-time processing**.** The proposed solution aims to improve defect detection accuracy, reduce reliance on human operators, and contribute to the automation of quality inspection processes in electronic component manufacturing.

2. Main Content

2.1 System Architecture Overview

The operating process of the MOSFET lead defect inspection system on trays is implemented through a closed-loop automated cycle that integrates a mechatronic motion mechanism with image processing algorithms. The schematic diagram of the system's operating principle is shown in **Fig. 1**.

The inspection process begins when the system is initialized. First, the two-axis X–Y motion mechanism is activated to move the camera or the component tray to predefined positions within the tray matrix. At each stopping position, the system captures images using an industrial camera for subsequent analysis.

The total inspection cycle time consists of three main components: mechanical movement time, image acquisition time, and AI inference time. In the current system, the average movement time between two adjacent positions is approximately 0.15–0.25 s, the image acquisition time is about 0.05 s, and the YOLOv8n inference time is approximately 0.02–0.03 s per image. This results in an average total processing time of approximately 0.25–0.35 s per inspection point, enabling the system to meet real-time industrial throughput requirements.

After the images are acquired, the detection algorithm based on a deep learning model is activated to determine the presence of a MOSFET component within the observation region. If no component is detected (i.e., the tray position is empty), the system skips the defect inspection step and moves to the next position on the tray.

If the system detects a MOSFET component, the captured image is forwarded to the processing module to inspect the condition of the component leads, such as bent, broken, or missing pins. The analysis results are then displayed directly on the monitoring interface and simultaneously stored for statistical analysis and quality evaluation.

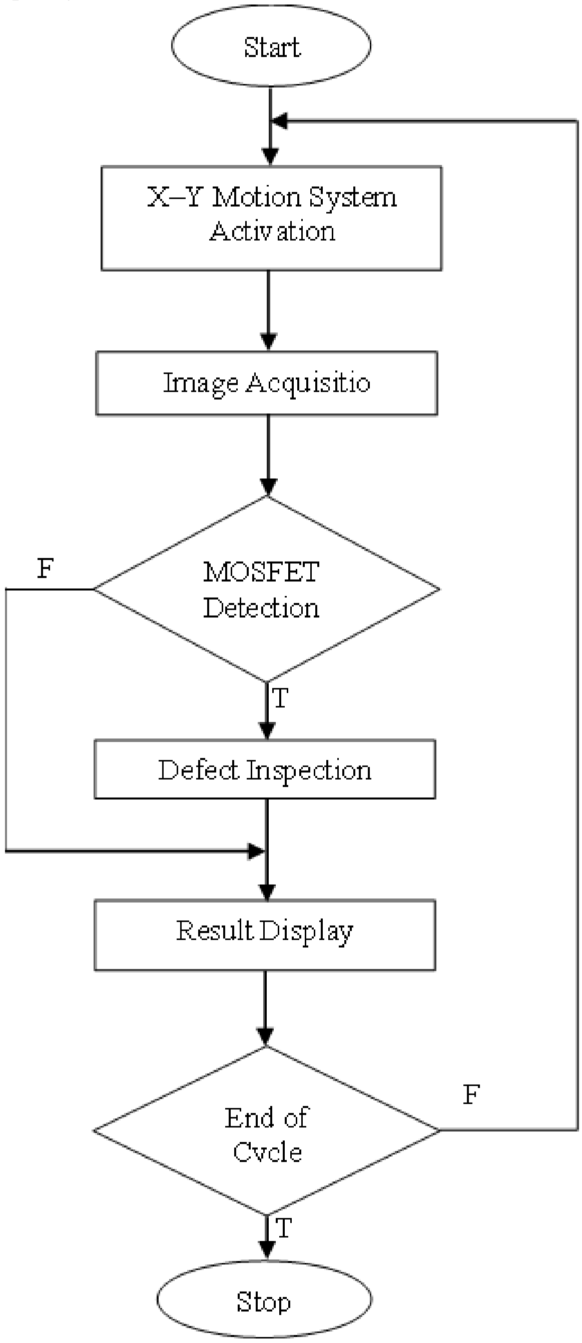


Figure 1. Overall operating diagram of the system.

After completing the inspection at a given position, the system checks the end condition of the scanning cycle. If all positions on the tray have been inspected, the process terminates. Otherwise, the system continues to control the X–Y motion mechanism to move to the next position and repeats the inspection steps until the entire scanning cycle is completed.

This cyclic operating mechanism enables the system to automatically, accurately, and continuously inspect all components on the tray, thereby meeting the quality inspection requirements in electronic component manufacturing lines.

2.2 Mechatronic and Optical Architecture for Image Acquisition

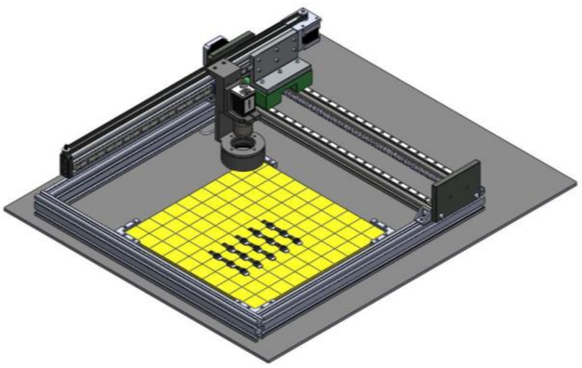


Figure 2. Overall 3D design of the system.

The system (Fig. 2) is designed to automatically scan, capture images, and inspect the lead condition of MOSFET components arranged on a tray in a matrix configuration. A standard tray integrated into the system contains up to 144 positions, arranged in 12 rows and 12 columns (12 × 12). Each component is placed in a dedicated slot on the tray to ensure stable positioning during image acquisition and inspection.

The X–Y motion system forms the foundation of the scanning and positioning process on the tray. The motion platform achieves a positioning resolution of approximately 0.05 mm and a repeatability of ±0.02 mm. The system operates with a trapezoidal velocity profile, with a maximum speed of 150 mm/s and controlled acceleration to minimize vibration during start–stop transitions. These specifications ensure sufficient precision for detecting small-scale defects on MOSFET leads. The mechanism is constructed using an industrial aluminum extrusion frame to ensure structural rigidity and minimize deformation during operation. The transmission system employs a steel-core timing belt combined with stepper motors, which helps reduce slippage and maintain positioning accuracy.

The joints and mounting brackets are manufactured using 3D printing technology, allowing optimization of mechanical structures and helping to reduce vibration during motion. The motor control system operates in microstepping mode and incorporates appropriate acceleration and speed control to improve positioning accuracy and ensure repeatability across the scanning coordinate grid.

The system operates through a sequential scanning cycle based on the X–Y motion coordinate system. The motion mechanism controls the camera to move sequentially to each position in the tray matrix. At each predefined coordinate, an interrupt signal is triggered to initiate the image acquisition process, and the captured image is transmitted to the central processing unit. The image data are then processed by the YOLOv8n detection model for analysis and evaluation.

The image acquisition system uses a high-resolution industrial camera from Basler, mounted on the horizontal rail of the X-axis to ensure that the field of view covers the entire inspection area. The camera provides the input image data required for the detection and defect analysis process.

To improve image quality and reduce the influence of ambient lighting noise, the system integrates an LED ring light surrounding the camera lens. The concentric illumination design enhances the contrast of the metallic surfaces of the component leads while minimizing shadows and dark regions.

In addition, the image acquisition process is synchronized with the stopping state of the X–Y motion system, ensuring that images are captured only when the motion mechanism has stabilized. This approach eliminates motion blur and improves the accuracy of the detection algorithm.

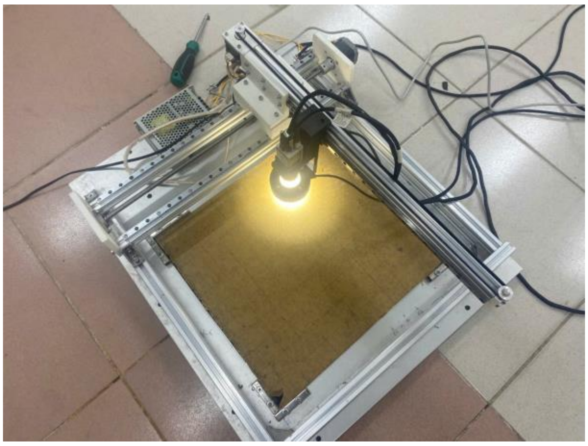


Figure 3. Actual prototype of the system.

Based on the classification results of the model, the system provides two processing states:

- Empty tray state (Empty): If the model does not detect the presence of a MOSFET component at the inspected position, the system labels that position as Empty. The information is updated on the monitoring interface, and the X–Y mechanism moves to the next position to minimize unnecessary processing time.
- MOSFET detected state: When a component is detected, the input image is cropped to obtain the Region of Interest (ROI) focusing on the component leads. The cropped image is then processed by a geometric inspection module to

evaluate lead deformation or missing pins. The final result is classified into two states: OK (acceptable) or NG (defective).

The scanning and inspection process is performed in a zigzag trajectory across the entire tray matrix until all positions have been examined. This strategy ensures synchronized system operation, reduces motion travel time, and improves the efficiency of the automated inspection process.

Figure 3 illustrates the actual prototype of the MOSFET component inspection system after fabrication and assembly. The system is developed based on a mechatronic design integrated with computer vision technology to automatically perform scanning, image acquisition, and inspection of component lead conditions.

From the mechanical perspective, the system frame is constructed from industrial aluminum extrusion to ensure structural rigidity and reduce vibration during operation. On this frame, a two-axis X–Y motion mechanism is installed to control the translational movement of the camera module to predefined positions on the component tray. The transmission system uses stepper motors combined with a timing belt mechanism, enabling high-precision position control and reliable repeatability during scanning.

The image acquisition module consists of an industrial camera mounted on the moving bracket of the motion axis. The camera is oriented perpendicular to the tray surface to ensure clear image capture of the inspection region. In addition, the illumination system employs a ring-shaped LED light installed concentrically with the camera lens, providing stable and uniform lighting across the component surface. This lighting configuration enhances the visibility of the MOSFET metal leads while reducing shadows and lighting noise during image acquisition.

The component tray is designed in a matrix structure with fixed compartments, enabling precise positioning of each component during inspection. During operation, the X–Y motion system moves the camera to each corresponding tray position to capture images and transmit them to the central processing unit. At this stage, the detection algorithm based on the YOLOv8n model analyzes the images and determines the component status.

The practical implementation of the system demonstrates effective integration between mechatronic hardware and image processing algorithms, forming a high-accuracy automated inspection solution suitable for electronic component manufacturing lines.

2.3. AI-Based Detection and Localization Algorithm

During the inspection of MOSFET components on trays, the captured images often contain various background elements such as the plastic structure of the tray or other irrelevant details. Processing the entire image frame can significantly increase computational complexity and affect the inference speed of the system. Therefore, the problem of locating and isolating the Region of Interest (ROI) plays an important role in improving detection efficiency.

In this study, the YOLOv8n (You Only Look Once version 8 – nano) model is selected to perform the object detection task. YOLOv8n is a lightweight version of the YOLO family of models, optimized for real-time processing applications and edge computing devices. The model is capable of detecting and localizing objects in an image using a single inference pass, thereby significantly reducing processing latency.

For the component inspection task, the model is trained with two main classification classes:

- MOSFET: representing the presence of a MOSFET component within the observation region.
- Empty: representing an empty tray position where no component is present.

The data annotation process is carried out by assigning bounding boxes to objects in the images, as illustrated in Fig. 4. The labels are generated using the Roboflow platform, which helps standardize the dataset and export it in a format compatible with YOLO. After completing the annotation process, the dataset is divided into training and validation sets to support model training and evaluation.

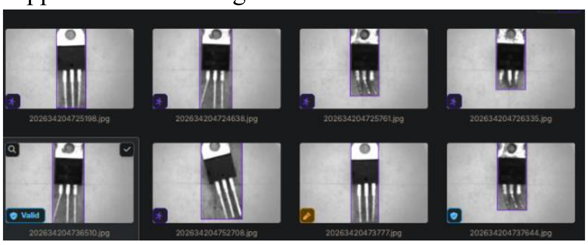


Figure 4. Data annotation and bounding box labeling for the dataset.

The model training process was conducted on the Google Colab platform with GPU acceleration to improve computational performance. The main hyperparameters (Fig. 5) were configured as follows:

- Input image size (imgsz): 640 × 640 pixels
- Number of training epochs: 50
- Batch size: 20
- Training device: GPU

During the training process, the YOLOv8n model learns to extract distinctive features that differentiate the plastic surface of the tray from the geometric characteristics of MOSFET components, particularly the metal lead region. These features are encoded into weight parameters within the deep neural network.

```
!pip install ultralytics
from ultralytics import YOLO
model = YOLO("yolov8n.pt")
results = model.train(
    data="/content/transistorDetection--5/data.yaml",
    epochs=50,
    imgsz=640,
    batch=20,
    device=0
)
```

Figure 5. Training configuration of the YOLOv8n model.

The training results are presented in Fig. 6. The loss functions gradually decrease as the number of epochs increases and begin to stabilize around epochs 10–15, indicating that the model progressively converges.

```
Epoch   GPU_mem  box_loss  cls_loss  dfl_loss  Instances   Size
 8/50     3.1G    0.9013    0.7404     1.167         29     640: 100% ────────── 33/33 3.3it/s 10.0s
         Class    Images  Instances    Box(P          R    mAP50  mAP50-95): 100% ────────── 3/3 2.2it/s 1.4s
           all       105       105     0.732      0.831    0.854      0.507

Epoch   GPU_mem  box_loss  cls_loss  dfl_loss  Instances   Size
 9/50     3.1G    0.8707    0.6943     1.169         27     640: 100% ────────── 33/33 3.2it/s 10.4s
         Class    Images  Instances    Box(P          R    mAP50  mAP50-95): 100% ────────── 3/3 2.6it/s 1.2s
           all       105       105     0.929      0.997     0.99      0.782

Epoch   GPU_mem  box_loss  cls_loss  dfl_loss  Instances   Size
10/50     3.1G    0.8844     0.713     1.158         26     640: 100% ────────── 33/33 3.2it/s 10.3s
         Class    Images  Instances    Box(P          R    mAP50  mAP50-95): 100% ────────── 3/3 2.3it/s 1.3s
           all       105       105      0.96       0.99    0.992       0.79

Epoch   GPU_mem  box_loss  cls_loss  dfl_loss  Instances   Size
11/50     3.1G    0.8507    0.6602     1.139         31     640: 100% ────────── 33/33 3.2it/s 10.5s
         Class    Images  Instances    Box(P          R    mAP50  mAP50-95): 100% ────────── 3/3 2.5it/s 1.2s
           all       105       105     0.876      0.872    0.896       0.54

Epoch   GPU_mem  box_loss  cls_loss  dfl_loss  Instances   Size
12/50     3.1G    0.8609    0.6421     1.142         34     640: 100% ────────── 33/33 3.4it/s 9.8s
         Class    Images  Instances    Box(P          R    mAP50  mAP50-95): 100% ────────── 3/3 2.2it/s 1.3s
           all       105       105      0.98          1    0.994      0.846

Epoch   GPU_mem  box_loss  cls_loss  dfl_loss  Instances   Size
13/50     3.1G    0.8181    0.6099     1.148         31     640: 100% ────────── 33/33 3.4it/s 9.7s
         Class    Images  Instances    Box(P          R    mAP50  mAP50-95): 100% ────────── 3/3 1.7it/s 1.7s
           all       105       105     0.965      0.981    0.991      0.796

Epoch   GPU_mem  box_loss  cls_loss  dfl_loss  Instances   Size
14/50     3.1G    0.7867    0.5951     1.103         37     640: 100% ────────── 33/33 2.9it/s 11.4s
         Class    Images  Instances    Box(P          R    mAP50  mAP50-95): 100% ────────── 3/3 1.3it/s 2.2s
           all       105       105     0.981      0.999    0.993      0.808
```

Figure 6. Results of the training process.

After 50 training epochs, the model achieves high evaluation metrics:

- Precision: 0.997
- Recall: 1.000
- mAP@0.5: 0.995

In addition, the box loss, classification loss, and distribution focal loss values decrease steadily during the training process, demonstrating that the model improves both object localization and classification performance without significant signs of overfitting.

Thanks to its fast and accurate detection capability, the YOLOv8n model can be directly integrated into the automated inspection system, enabling real-time detection and localization of MOSFET components during the tray scanning process. The lightweight architecture ensures low inference latency, which is critical in maintaining the overall cycle time of the inspection system.

2.4. Image Processing and Geometric Condition Analysis

After the YOLOv8n model detects and localizes the object using a bounding box, the image region containing the MOSFET component is cropped to obtain the Region of Interest (ROI) for detailed analysis. This ROI image is then processed by the image processing module to evaluate the geometric condition of the component leads using computer vision algorithms.

a) Image Preprocessing

In the first step, the ROI image is converted from the RGB color space to a grayscale image to reduce data complexity and highlight intensity differences between image regions. Next, a Gaussian filter is applied to remove noise and smooth the image. This method helps eliminate small noise points and improves the stability of subsequent processing steps.

b) Image Segmentation

After preprocessing, a thresholding algorithm is used to convert the grayscale image into a binary image. In this binary representation, high-intensity regions—corresponding to the metallic leads of the MOSFET—are clearly separated from the darker background of the plastic tray or the component body. This segmentation process highlights the features of interest and facilitates subsequent edge extraction.

c) Contour Extraction

Next, the FindContours algorithm from the image processing library is used to identify the boundaries of objects in the binary image. This algorithm accurately determines the geometric edges of the component leads, resulting in a set of contours that represent the shapes of the objects in the image space.

d) Geometric Feature Analysis

Based on the extracted contours, the system analyzes the geometric characteristics of the MOSFET component to determine the condition of its leads. Under normal conditions, a MOSFET should have three parallel metallic leads with relatively uniform size and spacing. If the geometric features satisfy the predefined criteria, the component is labeled as OK (acceptable).

In this study, the classification between OK and NG states is determined based on quantitative geometric criteria. First, the length of each lead is measured from the extracted contour. If the length of any lead is smaller than 0.9 times the reference standard length (i.e., ($L_i < 0.9L_{ref}$)), the component is classified as NG due to a broken or shortened lead.

Second, the reflective intensity region (white region) on the metallic lead is analyzed. If the detected bright region area is smaller than 0.9 times the expected standard area (i.e., ($A_i < 0.9A_{ref}$)), the lead is considered defective, indicating possible surface damage or incomplete structure, and the component is labeled as NG.

Third, the curvature of the lead is evaluated based on the contour shape. If the curvature or bending radius of the contour exceeds a predefined threshold (i.e., the fitted contour deviates significantly from a straight line), the lead is considered bent. In this case, the component is also classified as NG.

Conversely, if deviations such as bent, broken, misaligned, or geometrically deformed leads are detected, the shape parameters of the contours will change significantly. To improve robustness against specular reflections on metallic leads, an adaptive thresholding method combined with morphological closing operations is applied. This approach helps reduce contour fragmentation caused by high-intensity reflections and ensures more stable contour extraction under varying lighting conditions.

For tray positions where no component is present, the system skips the geometric analysis step and assigns the status Empty.

Through this image processing and geometric analysis procedure, the system can rapidly and accurately evaluate the condition of MOSFET component leads, thereby improving the effectiveness of automated inspection in electronic component manufacturing lines.

2.5. Software Interface Design for System Control and Monitoring

The system control and monitoring software is developed as a Human–Machine Interface (HMI) application named "Classificating Transistor." The application is implemented on the Microsoft .NET Framework platform using the C# programming language and the Windows Forms (WinForms) development environment.

The software architecture follows an event-driven model, in which events generated from the user, the camera, and the motion control system trigger corresponding processing functions. This design ensures flexible system operation and enables real-time response during the inspection process.

In the main interface of the software (Fig. 7), the control panel is located on the left side and includes the primary functional modules such as motion system connection and camera connection. The motion control module uses the Serial Port (UART) protocol to establish communication between the computer and the microcontroller responsible for controlling the X–Y axis motors. Through this interface, the operator can connect to or disconnect from the mechanical system. In addition, the Camera Connect module enables connection to the industrial camera via its Hardware ID, ensuring that a live image stream is available for component detection and inspection.

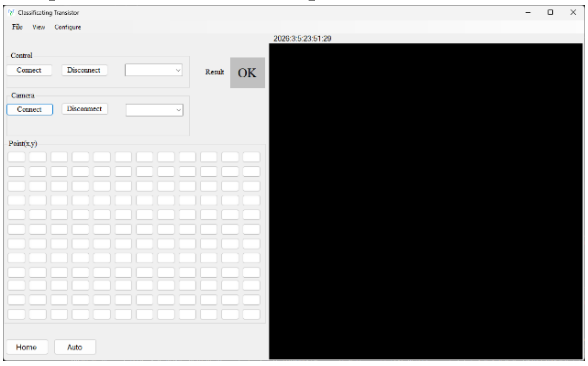


Figure 7. Control and monitoring software interface.

An important element of the interface is the tray matrix status panel, which is designed as a 12 × 12 grid, corresponding to the 144 component positions on the actual tray. Each cell in the matrix represents an inspection position and is updated in real time according to the analysis results of the computer vision system. The system status is represented using intuitive color codes:

- Green: The component at the inspected position meets the required standard and is labeled OK.
- Red: A defect is detected, such as missing leads, bent leads, or geometric deformation, and the component is labeled NG.
- White: The tray position is empty, indicating that no component is present.

In addition, the camera display area is located on the right side of the interface. This section shows the real-time video stream from the camera, allowing the operator to directly observe the scanning and inspection process. The system also supports the visualization of image processing results, such as the ROI region, binarized images, or detected contours, enabling engineers to monitor and adjust processing parameters when necessary.

To operate the system, the user simply activates the Auto mode on the interface. The software then automatically controls the X–Y motion mechanism to perform a sequential scanning cycle across the tray positions while simultaneously capturing images and performing detection using the YOLOv8n model. The analysis results are immediately updated on the tray matrix status panel, enabling operators to monitor the entire inspection process in a clear and continuous manner.

Thanks to its intuitive interface design and real-time data update capability, the HMI system not only supports efficient operation but also enhances monitoring and quality evaluation of electronic components in manufacturing environments.

3. Experimental Results and Discussion

The training results of the YOLOv8n model are evaluated using important performance metrics such as Precision, Recall, and mAP@0.5. Fig. 8 illustrates the variation of the mAP@0.5 metric with respect to the number of training epochs. It can be observed that during the initial epochs, the mAP value increases rapidly as the model begins to learn the fundamental features of the objects. After approximately 10–15 epochs, the curve gradually stabilizes and approaches a value close to 1.0. By the end of the training process, the mAP@0.5 reaches approximately 0.995, indicating that the model is capable of detecting and localizing MOSFET components with very high accuracy.

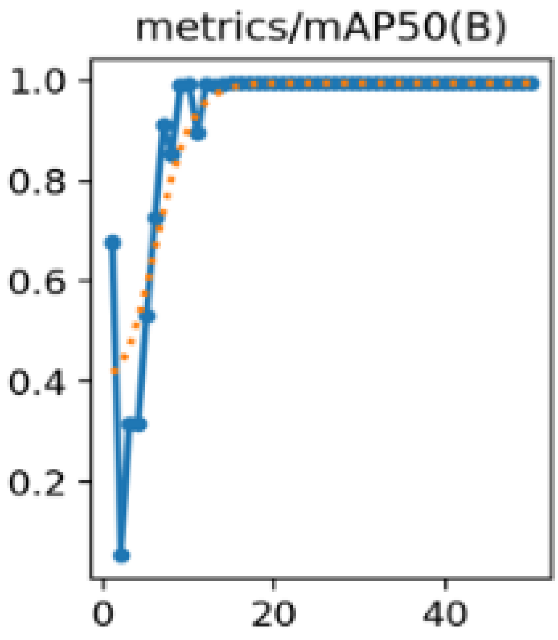


Figure 8. Model accuracy.

These results demonstrate that the YOLOv8n network effectively learns both the geometric features and intensity characteristics of the component leads while clearly distinguishing between the plastic tray background and the target objects. This capability is particularly important in real-world environments, where images may be affected by factors such as shadows, light reflections, or background noise.

Fig. 9 illustrates the variation of the localization loss function (val/box_loss) during the training process. It can be seen that in the initial stage, the loss value is relatively high because the model has not yet learned the positional features of the objects. However, after several epochs, the loss decreases rapidly and gradually converges to a stable level.

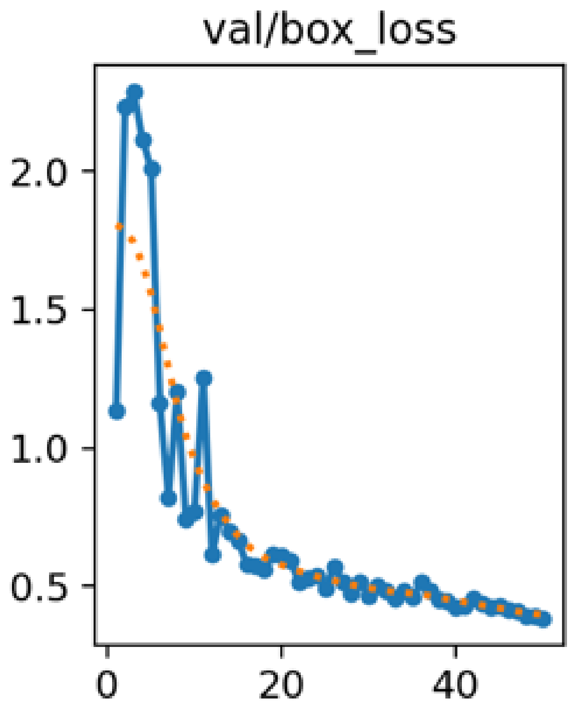


Figure 9. Model loss.

At the end of the training process, the box_loss value decreases to approximately 0.4, indicating that the model has significantly improved its ability to predict the position of the bounding boxes. This implies that the system can determine the location of components in the image with small error, ensuring high accuracy during the inspection process.

When deployed in the experimental system, the inspection cycle time is quantitatively evaluated. Due to the trapezoidal velocity profile and controlled acceleration used to ensure positioning stability and minimize vibration, the mechanical movement time is slightly increased compared to ideal conditions. The average processing time per component is approximately 0.32–0.35 s, including 0.22–0.25 s for mechanical movement, 0.05 s for image acquisition, and 0.05 s for AI inference and geometric analysis.

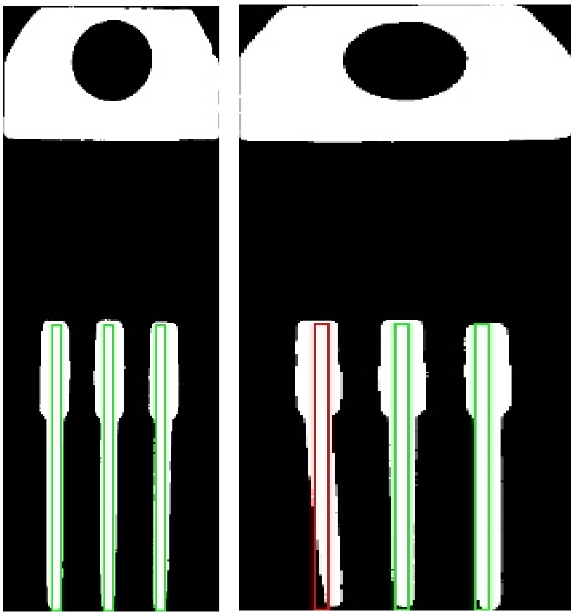
Therefore, the total time required to inspect a full tray of 144 components is approximately 46–52 seconds, which satisfies real-time industrial inspection requirements while maintaining high positioning accuracy (0.05 mm resolution and ±0.02 mm repeatability).

When deployed in the experimental system, the model demonstrates stable performance under real operating conditions. The system can sequentially scan the entire tray containing 144 component positions with high processing speed and low latency. Moreover, the practical inspection results show that the image processing algorithm combined with the YOLOv8n model can accurately identify the states of qualified components (OK), defective components (NG), and empty positions (Empty).

To further evaluate detection performance, a confusion matrix is constructed based on a test dataset of labeled samples. The results indicate that the system achieves an overall accuracy above 99%, with defect detection rates of approximately 97.7% for bent leads and 96% for missing leads. The false positive and false negative rates remain below 1%, demonstrating the reliability of the proposed approach under practical conditions.

In addition, the geometric inspection process based on contour extraction from binary images shows high stability. In practical experiments, the system did not record significant errors such as false positives or false negatives, demonstrating that the proposed method can reliably detect defects in component leads.

These experimental results confirm that the MOSFET component inspection system based on computer vision and the YOLOv8n model can effectively satisfy the requirements of accuracy, processing speed, and operational stability, making it suitable for automated inspection applications in electronic component manufacturing lines.



a) b)

Figure 10. nspection of MOSFET lead conditions: (a) straight leads; (b) bent leads

After the YOLOv8n model detects and localizes the MOSFET component, the image region containing the component leads is extracted for geometric analysis. This process aims to evaluate the condition of the leads and detect defects such as bent leads, misalignment, or geometric deformation.

In the processing stage, the Region of Interest (ROI) image is converted into a binary image to highlight the metallic leads against the background of the component body. Next, a contour detection algorithm is applied to determine the shape and boundaries of each component lead. Based on these contours, the system analyzes several geometric features, including straightness, orientation angle, and uniformity among the leads.

The results illustrated in Fig. 10 show two different inspection cases. In the first case, the component leads are straight, parallel, and evenly aligned; therefore, the system marks their contours with green boundaries, indicating that the component meets the required standard. In contrast, in the second case, one of the leads is bent or deviates from the reference axis, causing a noticeable change in the contour shape. When such a deviation is detected, the system marks the defective lead with a red boundary, while the remaining acceptable leads are still displayed in green.

This geometry-based inspection method enables the system to quickly detect mechanical defects in component leads, thereby improving the accuracy of the automated inspection process. Combined with the YOLOv8n object detection model, the system can simultaneously perform component localization and MOSFET lead quality assessment, ensuring effective inspection capability for electronic component manufacturing applications.

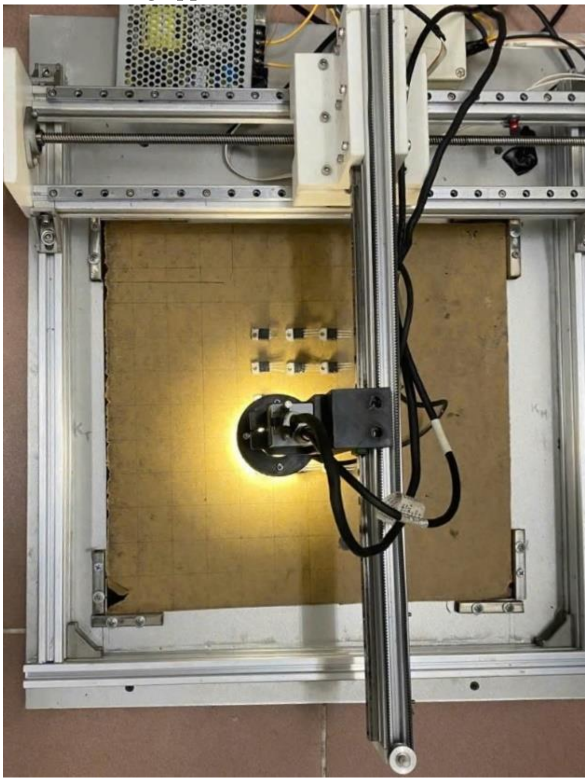


Figure 11. Inspection model at a defective component position.

After the system completes the scanning process at each position on the component tray (Fig. 11), the recognition results are displayed directly on the monitoring interface of the software. The scanning process is performed sequentially in a row–column order across the 12 × 12 tray matrix, corresponding to 144 inspection positions. At each position, the X–Y motion mechanism stops to capture an image, after which the system performs detection using the YOLOv8n model and conducts geometric analysis of the component leads.

Figure 12. Detection results of defective components.

The inspection results are presented simultaneously in two areas of the interface. The first is the camera display area, where the detection model highlights the component using a bounding box. If the component meets the required standard, the detection box is displayed in green, as shown in Fig. 13. Conversely, when defects such as bent leads, missing leads, or geometric deformation are detected, the system displays the detection box in red and assigns the NG status, as illustrated in Fig. 12.

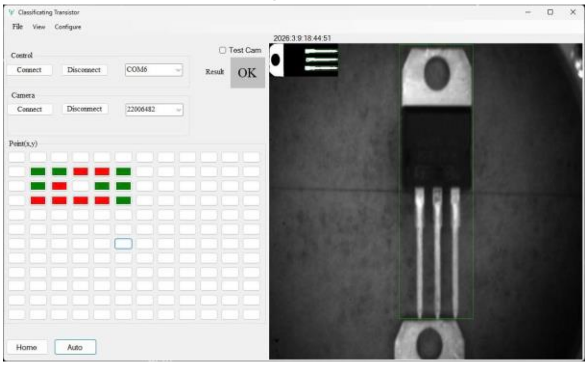


Figure 13. Detection results of acceptable components.

The second area is the tray matrix status panel, where each cell represents a corresponding component position on the tray. As the system scans each position, the status cell is updated in real time using intuitive color codes:

- Green: acceptable component (OK).
- Red: defective component (NG).
- White: empty position with no component present.

This visualization method allows operators to quickly observe the overall status of the component tray during the inspection process without monitoring each image individually. Furthermore, updating the status sequentially according to the row–column scanning order enables intuitive tracking of the system operation and helps quickly identify the position of defective components on the tray.

Experimental results show that the system can scan and recognize all components on the within approximately 40–45 seconds per full cycle, while displaying the results clearly and accurately on the monitoring interface. This demonstrates the applicability of the proposed system for automated electronic component inspection lines.

4. Conclusion

This study successfully developed an automated inspection system for MOSFET components based on the integration of computer vision and the YOLOv8n deep learning model. The system consists of an X–Y motion mechanism, an industrial camera, image processing algorithms, and an HMI monitoring interface developed using the C# programming language. The YOLOv8n model is employed to detect and localize components, while a contour-based analysis method is applied to evaluate the geometric condition of the component leads.

Experimental results demonstrate that the proposed system achieves high accuracy, with Precision = 0.997, Recall = 1.0, and mAP@0.5 = 0.995. The system is capable of scanning the entire 12 × 12 tray and displaying inspection results in real time, effectively identifying both acceptable and defective components. The proposed approach shows strong potential for application in automated electronic component quality inspection lines. In future work, the system can be further extended by integrating robotic systems to enable automatic sorting and handling of defective components in smart manufacturing environments.

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