Deep Learning Enables Intelligent Defect Detection and Interception in LCD Manufacturing

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Abstract

Conventional LCD panel inspection methods struggle to identify subtle defects, such as progressive and clustered flaws. This paper proposes a deep learning-based system to address these limitations, enhancing defect detection and repair capabilities. Our system aims to improve quality control, reduce waste, and deliver higher quality products.

Author Keywords

Image Deep Learning; Defect Detection; Process Quality Control; Defect Repair; Manufacturing

1. Introduction

In the competitive landscape of panel manufacturing, even the slightest defect can have major consequences. Product defects arise from factors including equipment performance fluctuations, aging components, environmental changes, and human activity. These defects manifest in diverse morphologies and impact product performance to varying degrees.

Effective defect detection and categorization are crucial for improving yield. Defect information is essential for analyzing defect root causes, implementing corrective actions, reducing material waste, and enhancing product quality.

Traditional defect detection methods include optical inspection based on image difference comparison and electrical testing based on voltage signal difference comparison. While both approaches have strengths and weaknesses, their ability to detect defects in non-regular regions is often insufficient.

Although equipment manufacturers continuously improve hardware and algorithms, a significant proportion of defects still escape detection. This cumulative effect across various processes leads to substantial material waste. Moreover, implementing new equipment and algorithms on existing systems is often costly or infeasible.

This paper proposes a low-cost solution leveraging image deep learning and data processing techniques, integrated with factory repair workflows. Our approach addresses the limitations of optical inspection (high data volume, low effective defect rate, and high manual review costs) and electrical testing (potential for false negatives). Achieve a highly efficient and intelligent defect detection and repair system. Normal implementation can improve defect leakage by 50%, ultimately leading to enhanced customer satisfaction. This innovative approach has the potential to revolutionize defect detection in panel manufacturing, leading to significant improvements in efficiency and product quality.

2. Method

This paper investigates the application and effectiveness of image deep learning and data processing techniques for intelligent defect detection and repair intervention in LCD manufacturing. Given the diversity of LCD products, this study focuses on two representative process enhancement approaches:

(a)Electrically-Tested Products: For products routinely inspected using electrical testing, the proposed method enhances defect identification and localization accuracy.

(b)Products Lacking Electrical Testing: For products without established electrical testing procedures or with low electrical testing detection rates, the method provides a robust alternative for defect detection and repair.

Subsequent sections outline system operations and workflow integration by product category:

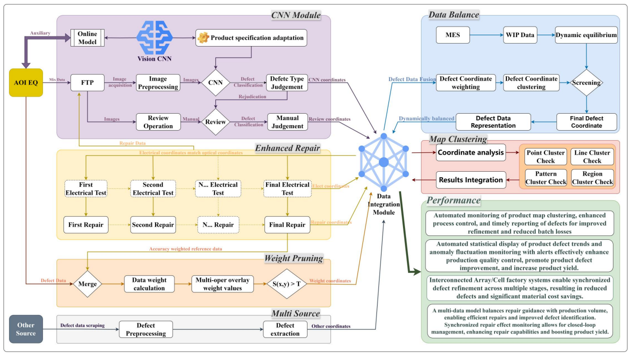

Figure 1. Illustration of System Functional Effects

2.1. Basic Information Investigation and Analysis: This section involves a thorough investigation of existing defect detection, repair, anomaly interception, and data transfer methods for corresponding products in factory manufacturing facilities. Based on the basic information analysis, the system's implementation approach and scope can be clearly defined. Since the factory already has repair mechanisms and utilizes process AOI (Automated Optical Inspection) data detection, the system can be implemented cost-effectively and comprehensively. If existing repair methods are absent, partial functionalities can still be applied, though full implementation might require additional investments in functional equipment.

2.2. Targeted Implementation Strategy Design: Based on the research data and application goals, a specific implementation strategy will be designed. The system's simplified implementation process will leverage existing equipment capabilities and production data to minimize additional investment costs.

For the two product types with significant differences, our system solutions will be applicable when process AOI image detection is available, considering the factory's existing business logic. Here's a breakdown of the process differences:

(a)Relies on Electrical Testing for Repair: This type can fully utilize the enhanced repair process within the blue box (Reference Figure 2), incorporating conventional electrical testing data, merged data, and data integrated through the Data Integration Module for enhanced defect repair.

(b)Limited or No Electrical Testing: For products with no electrical testing repair process or low electrical testing detection rates, the Electrical Test process within the blue box (Reference Figure 2) can be skipped. Data integration using the Data Integration Module can directly enhance repair. If a Repair process is absent, adding repair equipment is recommended. If

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the Enhanced Repair process is not feasible, the system will still significantly contribute to process monitoring and defect interception.

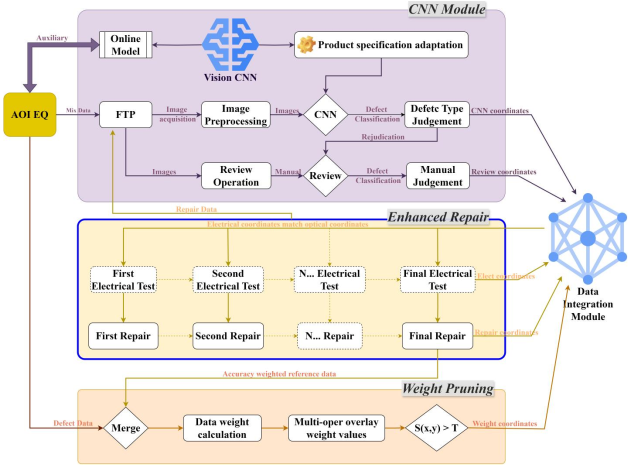

Figure 2. Differential Application of Enhanced Repair

It is estimated that the system can adapt and meet process monitoring and repair enhancement needs in other scenarios.

2.3. System Integration: Module Introduction

2.3.1. CNN Module:

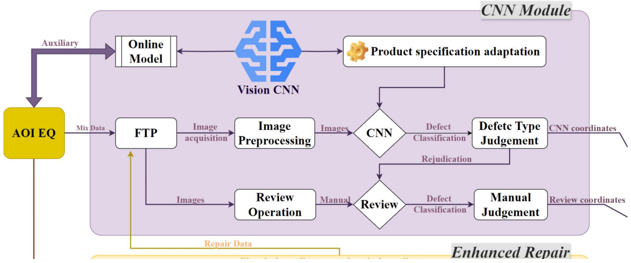

Figure 3. CNN Module's Workflow Diagram

This module processes image data using a Convolutional Neural Network (CNN), further obtaining classified defect information and coordinate information for downstream functionalities, which consists of convolutional layers, pooling layers, and fully connected layers. Convolutional layers extract local image features using convolutional kernels, while pooling layers reduce feature map dimensionality. Fully connected layers perform classification or regression tasks using deep learning.

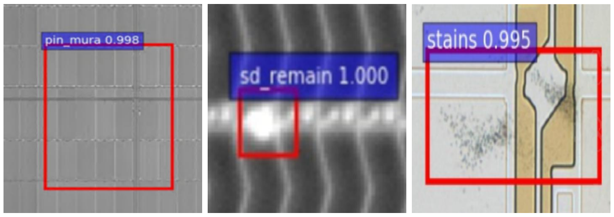

Figure 4. Defect Recognition and Localization Diagram

The module utilizes established frameworks like YOLO, Faster R-CNN, Mask R-CNN, and their variants for defect learning. A distributed underlying system and synchronized hyperparameter scheduling accelerate training, enabling single sessions to complete in under 3 hours. Data category matching and automatic download tools facilitate efficient multi-person collaborative annotation, allowing for rapid deployment of new defect models. This functionality includes automatic image classification based on pre-trained models, identifying potential defect types and accelerating the annotation process.

The CNN model can directly integrate with AOI equipment, enhancing the accuracy of AOI's defect analysis algorithms at the data source. It can also perform image marking and targeted re-captures for defects of interest, improving data detection comprehensiveness and effectiveness.

The model processes the final results of AOI detection data and integrates them with manual review results. Through data comparisons and synchronized supervision, the accuracy of both the CNN model and manual reviews is further enhanced. The result achieves an accuracy of $\geq 98\%$, with a single image evaluation time of ≤ 20ms, enabling efficient full image coverage in factories. Finally, the Data Integration Module consolidates and distributes the optimized results.

2.3.2. Enhanced Repair：

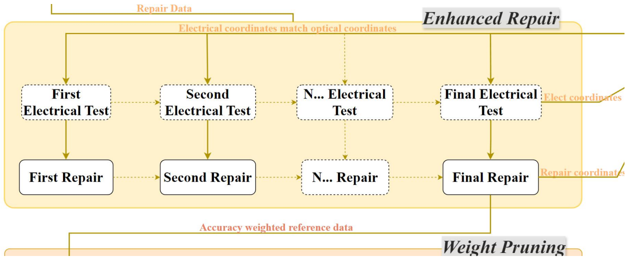

Figure 5. Enhanced Repair Workflow Diagram

This module closely collaborates with the Data Integration Module, utilizing combined defect data to enhance the repair process. Images captured during the repair process are monitored by the CNN Module for effectiveness and by human reviewers for quality assurance. Test and repair results are analyzed by the Weight Pruning Module, which evaluates and matches data weights to optimize AOI data utilization. The insights gained are fed back into the repair process for continuous improvement.

This closed-loop management approach ultimately leads to higher product repair yields under the system's guidance.

2.3.3. Weight Pruning：

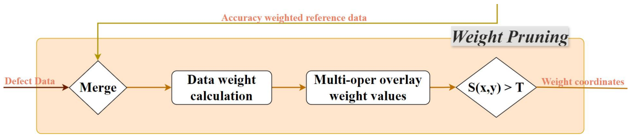

Figure 6. Weight Pruning Workflow Diagram

This algorithm aims to identify high-probability defect locations by analyzing defect data from multiple AOI stations. It leverages historical defect coordinates and assigns weights to each AOI station based on their correlation with known defect locations.

Stations with stronger correlations (more defects at the same coordinates) are assigned higher weights. These weights are summed for each coordinate, and if the total exceeds a threshold (T), the coordinate is flagged as a high-suspect defect location. Simplified Algorithm: The weight (W_i) for each AOI station (i) is computed using the formula:

$$W_i = \alpha \times R_i + \beta \times E_i \qquad (1)$$

α and β are weight coefficients that require algorithmic adjustment based on the specific application.

R_i: Represents the ratio of defect coordinates from station i that overlap with known defect locations.

$$R_i = |C_i \cap D|/|D| \tag{2}$$

C_i: Set of defects detected by station i.

D: Set of known defect locations.

E_i: Represents the ratio of effective defect reports from station i to the total number of defect reports.

$$E_i = V_i/P_i \tag{3}$$

V_i: Number of valid defect reports from station i .

P_i: Total number of defect reports from station i .

The final suspect defect probability ($S(x,y)$) for a given coordinate (x,y) is calculated by summing the weights of all AOI stations at that coordinate:

$$S(x,y) = \sum_i^n W_i(x,y) \tag{4}$$

If $S(x,y)$ surpasses the threshold (T), the coordinate is flagged for further processing and potential repair in the Data Integration Module.

2.3.4. Multi Source：

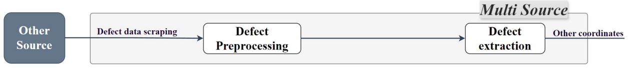

Figure 7. Multi Source Workflow Diagram

This module is primarily responsible for capturing and preprocessing defect data from other sources within the existing system. It consolidates this data and sends it to the Data Integration Module for further processing and practical application.

Essentially, the Multi Source module expands the range of defect data sources, thereby enhancing the system's data extensibility and overall effectiveness.

2.3.5. Data Balance：

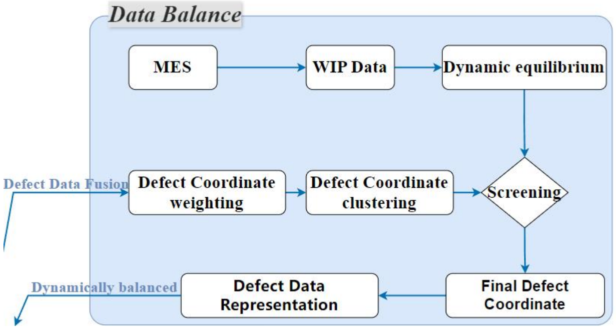

Figure 8. Data Balance Workflow Diagram

Data Balance is the heart of the Data Integration Module's data processing. This section addresses the critical challenge of integrating diverse defect data from various sources while maintaining a balance between production efficiency and defect identification accuracy. The system receives defect data from image processing, human inspectors, automated quality control systems, and potentially existing electrical testing or manual inspection equipment.

To tackle this challenge, a robust Data Integration and Filtering Algorithm is employed. It begins with preprocessing the raw data to standardize formats, remove errors and duplicates, and ensure consistency in coordinate systems. Next, defect weights are calculated by assigning weights to different data sources based on their accuracy and reliability. These weights are further refined based on the type and severity of the defect and the proximity of other defects.

The algorithm then fuses the data from different sources using methods like weighted averaging, voting mechanisms, and clustering algorithms to determine the final defect coordinates. Finally, a data volume control mechanism utilizes a defect probability threshold, dynamically adjusted based on production demands and quality goals. This ensures that the system can prioritize high-probability defects during periods of high production demand, while increasing the inspection volume when production is less demanding.

By implementing this comprehensive approach, the system achieves a balanced flow of defect data, optimizing both production efficiency and quality control.

2.3.6. Map Clustering：

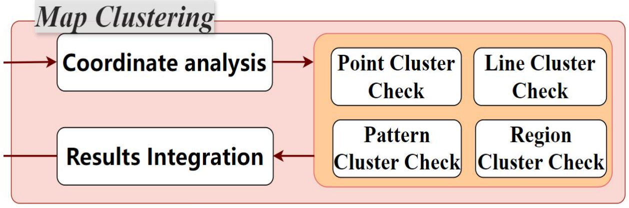

Figure 9. Map Clustering Workflow Diagram

The Map Clustering component relies on balanced defect data from the Data Integration Module, utilizing advanced algorithms to identify individual defects, as well as defect patterns and clusters. This facilitates the detection of potential production issues that might otherwise be overlooked.

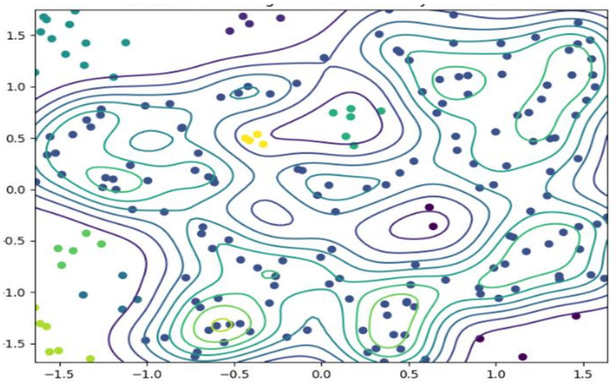

Figure 10. Map Clustering Diagram

The clustering process groups defect points based on their proximity and characteristics using techniques like density-based or hierarchical clustering. The system then analyzes these clusters by examining their shape, orientation, location within the product, and cross-referencing with historical data to determine defect types and potential causes. For example, clusters observed near the edges of the product may exhibit a strong correlation with specific historically known process stages, enabling data engineers to swiftly identify the root causes of anomalies. This also assists equipment engineers in quickly pinpointing faulty equipment, thereby accelerating anomaly resolution and improving efficiency.

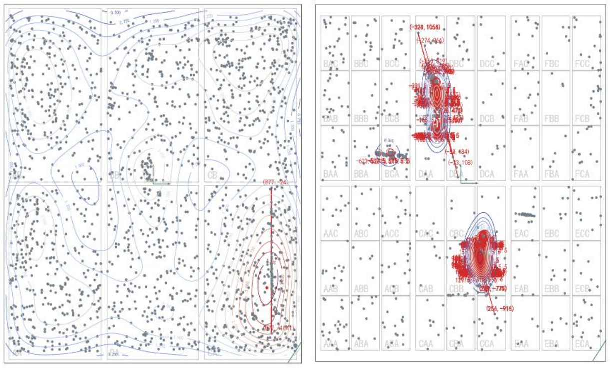

Figure 11. Regional Aggregation Improves Anomaly Detection (Red Regions)

Based on the severity and type of the clustered defect, the system generates alerts. High-severity clusters trigger immediate alerts, indicating a potential production issue requiring immediate attention. Lower-severity clusters trigger delayed alerts, allowing for further investigation.

Importantly, the results of the Map Clustering analysis are fed back to the Data Integration Module, creating a closed-loop system for continuous improvement. This feedback loop allows the system to constantly refine its defect detection and analysis capabilities. This also assists equipment engineers in quickly pinpointing faulty equipment, thereby accelerating anomaly resolution and improving efficiency.

3. Application Effects

Real-world implementation has definitively proven the efficacy of deep learning for image-based defect analysis in LCD manufacturing. As detailed in Table 1, the system delivers a remarkable 65% improvement in peripheral defect detection, a 53% reduction in false positives, and a substantial 20-40% decrease in the scrap rate of defective panels. While a slight increase in average repair time is observed, the net effect on overall product quality control is decidedly positive, underscoring the system's value in enhancing manufacturing efficiency and reducing waste.

Table 1. Partial Application Effects

Scope	Metric	Base	System	Δ (%)
Periphery Defects	Interception Rate	10%	75%	65
False Positive	Misclassification Rate	3%	1.4%	53
Material Waste	Panel Scrap Rate (With Suspected Defects)	40-100%	20-60%	20-40
Repair Workflow	Avg Repair Time	1 h	1.1 h	-10

Referring to Table 2, this deep learning system has wide-ranging advantages across various products. It can achieve targeted defect interception or repair according to the differences in product defects. (Statistical system implementation related defects: module highlights in TVs reduced by 40%, module line defects in laptops reduced by 55%) and it simplifies the manufacturing process of mobile devices (process monitoring time shortened from 20 days to 1 day).

Table 2. Defect Matching & Product Improvements

Product	Benefit	Improvement
Televisions	Fewer Defects	40%↓ module highlights
Notebooks	Fewer Defects	55%↓ module line defects
Mobiles	Efficient Production	20-1day process time, 1.5%↑ yield
Array Products	Higher Yield	0.4 - 1.7%↑ yield
Cell Products	Better Quality	Early defect warnings, 200% ↑ targeted inspections

For yield improvement, Array products' yield increased by 0.4% to 1.7%, while mobile device clients' yield rose by 1.5%. Enhanced data integration and system linkage boosted defect interception in cell phone products by 200%, raising customer satisfaction.

4. Conclusion

This study successfully developed and deployed a deep learning system for LCD defect repair. Real-time process data analysis enables significant cost optimization (e.g., a 20-40% reduction in the scrap rate of defective panels) and enhanced quality control, as evidenced by a 40% reduction in TV module highlights and a 55% reduction in laptop module line defects. Building on this success, the system further demonstrates its effectiveness through functionalities such as Better Process Control, Coordinated Repairs, and Smart Repair Guidance, proving its effectiveness and utility in LCD manufacturing.

Looking ahead, we will continue to optimize and expand the system's functionality. By integrating a broader range of process and yield data into our deep learning models, we aim to achieve more comprehensive defect detection and repair guidance. This will drive further improvements in product quality and efficiency, ultimately leading to significant advancements across the industry. Our goal is to empower manufacturers to create higher-quality and more competitive products.

5. References

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