LCD Defect Detection Based on Deep Learning and MapReduce

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Abstract. With the rapid development of the optoelectronic communication industry, the requirements for accuracy and efficiency in LCD defect detection are increasing. This paper takes LCD defect detection as the research object, analyzes the principles and performance advantages and disadvantages of three types of algorithms, and introduces the MapReduce distributed computing framework to explore its optimization ideas in LCD defect detection. Comparative analysis reveals that single-stage models offer strong real-time performance but have limited ability to detect subtle defects; two-stage models achieve higher accuracy but suffer from high computational complexity and slow inference speed; combining MapReduce with traditional models can effectively improve the processing efficiency of large-scale detection tasks. Research indicates that the combination of distributed computing and deep learning-based object detection can significantly improve efficiency while maintaining detection accuracy, providing a feasible technical path for improving the speed and accuracy of LCD defect detection.

Keywords: Liquid crystal defect detection, MapReduce, YOLO, SSD, R-CNN

1 Introduction

With the development of the optoelectronic communication industry becoming more and more mature, the demand for defect detection of the liquid crystal production line is also growing, while the detection speed and accuracy of many original defect detection schemes need to be improved. At present, LCD is widely used in the fields of Internet of Things, smart home, medical and health care, living and office supplies, communication equipment, vehicle electronics and so on. The quality of LCD can directly affect the reliability of terminal equipment. However, LCD is prone to edge collapse, damage, cracks, scratches and other defects in actual production. If these defects are not handled in time, it is very likely that the broken glass inside the equipment will affect the whole production line and eventually lead to economic losses. Therefore, the defect detection process with timeliness and accuracy is particularly important.

The traditional ways of artificial defect detection have many disadvantages such as being harmful to human eyes, having difficulty recruiting workers, the subjectivity of manual detection, instability of product quality, the LCD defects cannot be counted digitally and so on.

ICIAAI 2026, May 22-24, Singapore, Singapore

DOI 10.4108/eai.22-5-2026.2365239

The defect detection based on a deep learning algorithm can make up for the above shortcomings. Furthermore, the algorithm can improve the production efficiency of the overall production line. This article will mainly introduce the three most commonly used series of methods.

On the basis of traditional algorithms, MapReduce is becoming a new research trend. Xiaxiaoyun and others studied the use of Hadoop based MapReduce framework to achieve LCD defect detection. Meng Lu and others found that using the MapReduce framework can improve the detection processing speed of the glass production line by 14.1% [1].

This paper studies the trend of combining big data models with industrial defect detection in recent years, mainly listing the cases of using a deep learning network to deal with liquid crystal defect detection, comparing the different detection methods, and showing the prospect of applying MapReduce technology to liquid crystal defect detection. This study provides a reference for further research on improving deep learning algorithms for defect detection.

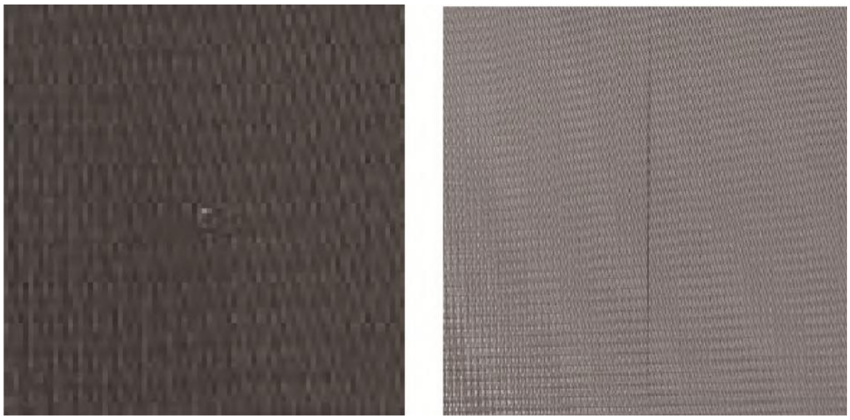
2 Categories of Liquid Crystal Defect Detection

Liquid crystal defect detection can be mainly classified in three ways [2]: classified by the causes of defect formation, classified by defect size, and classified by defect shape (Figure 1).

According to the causes of defects, defects are classified into electrical defects and non-electrical defects. Abnormal conditions such as short circuit, open circuit, abnormal driving and poor voltage line of the circuit may lead to electrical defects; non-electrical defects are caused by non-electrical factors, such as foreign matter in the board, uneven liquid crystal coating, etc.

According to the size of defects, defects can be divided into macro defects and micro defects. Macro defects have the characteristics of irregular size and shape, high contrast, and their factors include different layout colors, stains or uneven backlight. The size of micro defects is very small and difficult to detect, including pinholes, scratches and so on.

According to the shape of defects, defects can be divided into point defects, line defects and Mura defects. Point defects and line defects are electrical defects; Mura defects are non-electrical defects. Point defects include bright spot defects, dark spot defects and bad spot defects, which are classified according to the shape and area of defects. Similarly, the off-line defects are divided into bright-line defects and dark-line defects. Semiconductor Equipment and Materials International (SEMI) defines the mura defect as the imperfect display visible on the surface of the pixel matrix when the display works. Mura defect has its own quantization standard. This defect usually occurs due to factors such as low contrast, blurred edges, uneven brightness areas, and generally a larger area than a single pixel.



point defect line defect

Fig. 1. Schematic diagram of point defect and line defect [2]

3 YOLO Series

You only look once(YOLO) is an advanced single-stage target detection framework [3, 4]. Currently, it has undergone a version change from v1 to v13. It is one of the main algorithms used in liquid crystal defect detection. At present, there are many advanced algorithms in this field, such as LC-YOLO [5] and FS-YOLO [6]. Based on YOLOv10, LC-YOLO changes the convolution module on the neck network to the full-dimensional dynamic convolution odconv. FS-YOLO is based on YOLOv8n with the new design of the feature pyramid FPSC module.

YOLO algorithm is a typical one-stage target detection algorithm [3, 7]. It uses the regression problem to replace the detection problem. The first step of the YOLO algorithm is to resize the input image. Then it analyzes and processes the entire input image. From the coordinate information, YOLO can obtain confidence and category probability of the corresponding boundary box of the image. Next, it uses the convolution layer for the convolution operation, and finally uses the non-maximum linear suppression algorithm to process the operation result and output the final result.

The algorithms from YOLOv2 to YOLOv13 are based on the previous version of the algorithm [8]. By changing the backbone and other factors to complete the version iteration, the processing speed and accuracy are further improved. At the same time, the advantages of the previous version are retained. Among them, the recently proposed fs-yolo algorithm, Xu Sheng and others designed a new feature pyramid FPSC module, which captures the context information of different scales in the image through the convolution layer with different expansion rates, and uses the sharing mechanism to inhibit the growth of parameters [6]. Based on the C2f-KW module owned by KernelWarehouse, the FPSC successfully improves the feature expression ability and computational efficiency of the model. The detection head SAGHead is designed to reduce the number of model parameters through the feature sharing mechanism and optimize the synchronization improvement of accuracy and parameters through the group normalization strategy.

4 SSD Family Approach

Single-shot multibox detector (SSD) is a single-stage multi-scale target detection algorithm [9]. The algorithm uses multiple prior frames to make them predict from different feature layers to achieve the purpose of single-stage target detection. Although discarding the RPN structure will affect the accuracy, the detection speed has been greatly improved. SSD algorithm predicts on the last feature layer after a multi-layer feature extraction network. At this time, it shows less detailed information. The low-level feature map has a lower degree of abstraction and less detailed information is lost. Therefore, prediction on the low-level feature map is more convenient for small target detection. While the high-level feature map has a higher degree of abstraction, it can be used to extract the semantic information of the image and for large target detection.

Later, Chen Cheng and others further improved the accuracy of the SSD algorithm [10] by introducing the ResNet residual module [11] and the feature pyramid network structure (FPN) [12]. The RESNET residual module can well solve the network degradation phenomenon. Compared with the traditional linear structure, it is difficult to fit the identity map. The improved jump connection allows the model to choose to update itself. The residual structure makes up for the irreversible loss of information caused by high nonlinearity. The introduction of FPN increases the fusion between high-level features and low-level features, improves the detection accuracy with the help of the panet structure, and solves the problem of insufficient positioning information. The experimental results show that the improved SSD network has higher average detection accuracy for all types of liquid crystal defects than the popular models, such as Faster R-CNN and YOLOv3, in the same period.

5 R-CNN Series

R-CNN is a typical two-stage target detection algorithm, which combines AlexNet and the selective search algorithm [13, 14]. R-CNN contains three modules: The first uses a selective algorithm to extract thousands of region candidate boxes that may contain target objects from the target image. Then, the depth feature extraction based on CNN is performed, and the candidate regions are normalized and scaled to a fixed size for feature extraction. Finally, classification and regression, using AlexNet to input all the features of candidate regions into SVM for classification, and adjusting and classifying the data by using bounding box regression (bounding box regression) and non-maximum suppression (NMS), finally, regression results are obtained.

In 2015, Girshick et al. developed the Fast R-CNN algorithm [15]. The algorithm simplifies the SPP layer and designs a single-scale ROI pooling layer structure. When sampling the candidate region of the whole image, it changes to a fixed size, generates a feature map and inputs SVD for decomposition. From the RO I pooling layer, two vectors, softmax's classification score and bounding box's window regression, are obtained; The idea of a multitask loss function is proposed by using softmax instead of SVM.

In 2017, He et al. added a mask branch to Fast R-CNN to build the Mask R-CNN model [16]. When pictures are input, the deep convolution network in the model uses the RPN network of the original model to carry out candidate area tasks and target detection. He et al. pointed out that RolPooling's error will increase due to the need for multiple quantization operations, and it will also make the pixels of the image and features deviate. The introduction of RolAlign can solve this problem. RolAlign keeps the obtained features consistent with the input, uses a bilinear interpolation algorithm, and uses the method of calculating with four pixel values around the input image to improve the detection accuracy.

In 2024, Wangyuanzhi et al. designed the k-means algorithm to cluster the defective LCD marker boxes to obtain the appropriate length-width ratio and the number of anchor boxes, and applied the original data set to the improved Mask RCNN model to extract the features of the defective area and carry out training classification [17]. This method is based on transfer learning and an improved Mask R-CNN LCD defect detection method, which solves the problem that the traditional image defect detection method can not effectively use the feature information for high-precision detection and missing detection. Finally, an excellent result of 95.25% micro defect recognition was obtained.

6 MapReduce

Google first proposed the MapReduce model [18]. The model abstracts complex distributed computing tasks into two core functions: map and reduce, greatly simplifying the programming work and computing pressure. The map stage is responsible for processing the original data and converting it into key-value pairs. Each input data unit is processed independently to generate intermediate results. The reduce stage receives the output of the map stage, presses the key to group the data, and performs the reduction operation on each group of data, and finally generates the results.

Xia Xiaoyun et al. [19] proposed a new idea. Xia used the strong storage capacity of the Hadoop cluster distributed computing to process liquid crystal defect detection. In view of the local characteristics of high-resolution LCD image defects, Xia and others used the distributed defect detection method based on MapReduce. The map divided the high-resolution image into blocks and completed the defect detection of all images in parallel. Then the detection results were merged to reduce. This way can solve the problem of low efficiency of high-resolution image defect detection in traditional detection methods. Finally, the experiment running on the Hadoop platform shows that this method has a good efficiency improvement effect while completing defect detection.

7 Comparative Analysis

YOLO has greatly improved the detection speed by omitting the generation of the candidate region of the two-stage model. It can process a large amount of data in a short time and maintain a real-time response. Compared with other models, its network structure is relatively simple, but the operation of only dividing the image into fixed grids makes its precision not high enough, and the boundary box positioning is not accurate enough. However, the structure of YOLO is simple and easy to implement and optimize. Under the continuous optimization experiment, the optimization algorithm of YOLO can better meet the requirements of defect detection and make up for the original shortcomings now [3-8].

While the SSD model has the same processing speed as YOLO, it also has high accuracy [10-13]. However, there are still cases of missed detection, especially for small target detection. In addition, due to the cost of high precision, SSD needs to detect multiple feature maps, resulting in a large amount of computation. Yet, compared with YOLO, SSD still has the advantage of accuracy in small target detection. Therefore, SSD is still a better choice in the process of liquid crystal defect detection requiring high-precision detection.

R-CNN is a two-stage detection model different from the first two models [13-17]. Because the preselected region is generated, its accuracy is higher than that of the first two models, but the processing speed is slower. It has obvious advantages in dealing with small and dense targets, but it has high computational complexity and high requirements for hardware resources. However, in the high-precision defect detection process such as liquid crystal defect detection, the high accuracy of R-CNN detection still has a strong competitive advantage.

MapReduce can distribute training and preprocess target detection data sets, improve accuracy based on the first three models, and, more importantly, improve the speed of data processing and solve the problem that some models sacrifice processing efficiency for accuracy [18, 19].

8 Conclusions

This paper reviews the research on LCD defect detection technology, describes the defect classification methods, compares and analyzes some technical principles and characteristics of the three mainstream deep learning target detection algorithms(YOLO, SSD and R-CNN), and discusses the value of the MapReduce distributed computing framework in improving detection efficiency. According to the research, the traditional single-stage detection algorithm has the advantages of high speed and good real-time performance, but it is weak in complex scenes, such as small defects and low-contrast mura defects. The two-stage detection algorithm achieves higher detection accuracy through candidate regions and fine feature extraction, especially in the recognition of microdefects. However, this model complexity is high and the processing speed is slow, which makes it difficult to meet the requirements of a large-scale production line.

As a typical distributed computing model, MapReduce can process image segmentation in parallel through the map function and aggregate the detection results with the reduce function, effectively reducing the computational pressure caused by high-resolution images and a large amount of data on the production line, and can complement the existing deep learning detection model. The practical application results show that the distributed detection scheme based on MapReduce can significantly improve the data processing speed, and provide an effective way to solve the problem that accuracy and efficiency are difficult to take into account.

In general, liquid crystal defect detection will develop in the direction of high precision, real-time, distributed and lightweight in the future. By improving the network structure, optimizing feature extraction, introducing new mechanisms and other methods, combined with MapReduce and other distributed technologies, it is expected to further improve the processing efficiency of the detection model in the scene of liquid crystal defect detection, and provide more reliable technical support for the automatic quality detection of liquid crystal display panels.

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