Exploration and Application of Unknown Category Defect Detection Methods for Display Panels

Siyi Hu, Fengjian Liu*, Shuang Gou*, Xin Xiong**
***BOE Technology Group, Chengdu, China**

Abstract
Defect detection is crucial in the panel industry, especially for unknown defects that occur during the production process. In order to solve this problem, we propose a novel feature fusion method, the Foreground-background Same-scale Difference Attention (FBSSDA) fusion module. Improvements are made to YOLOv5, and the FBSSDA-YOLOv5 defect detection model is proposed to be applied to the production inspection of display panels. First, in the feature extraction stage, the model constructs a feature fusion module by introducing the FBSSDA attention mechanism to extract foreground and background difference features at the same scale; second, a contrast loss function is introduced to expand the differences between different defect categories; finally, an improved NMS algorithm, U-NMS, is proposed to increase the recognition of unknown defects.

Keywords
FBSSDA attention, Unknown category, Display panel defect detection.

1. Introduction
Traditional manual defect detection is time-consuming, has low accuracy, and is highly influenced by subjective factors. In contrast, artificial intelligence inspection technology based on deep learning has emerged to enable automated and intelligent inspection of display panel defects. This technology significantly improves production efficiency and product quality, becoming an important trend in the industry's development[1].

YOLOv5 is a deep learning object detection algorithm designed for detecting defects in display panels. While it performs well in identifying known defects, its effectiveness diminishes when faced with unknown defects. As materials and processes change, new defects continuously emerge, impacting product quality and productivity. Therefore, enhancing YOLOv5's ability to detect unknown defects has become an urgent technical challenge for the industry.

In response to this challenge, this paper proposes a new feature extractor called FBSSDA attention, which is applied to the feature extraction stage of YOLOv5. We introduce a novel defect detection method, FBSSDA-YOLOv5, designed to effectively identify unknown defects. The main contributions and innovations of this paper are as follows:

1. FBSSDA attention mechanism is proposed, and in the feature extraction stage of YOLOv5, FBSSDA is utilized to construct a feature fusion module to increase the weight of background-foreground differences, and to comprehensively consider the feature differences between the foreground and background regions at the same scale.
2. A contrast loss function is introduced to increase inter-class spacing and decrease intra-class spacing to effectively improve class separability, and a “One-vs-ALL” strategy is used to transform the multi-class classification problem into multiple binary classification tasks, improving the model's ability to distinguish between different classes while minimizing within each class the amount of Confusion.
3. Propose an improved NMS Algorithm U-NMS and updated prediction logic to increase unknown defect recognition.

2. Yolov5 model and Contrastive Loss
Yolov5 model: YOLO model[2] is an advanced deep learning object detection algorithm, which was first proposed in 2015 by Joseph Redmon et al.YOLO is mainly used in the field of object detection(machine vision subfield), and the recognition and localization of the objects in the image can be accomplished by a single view, which has the advantages of fast speed, high accuracy, strong interpretability and wide applicability, and it is the current object detection field It is one of the most important representatives of the current object detection field. Due to its fast and accurate characteristics, YOLO has been widely used in many fields, including intelligent manufacturing, medical and health care[3], automatic driving[4] and industrial quality inspection[5].

The YOLO model consists of Input, Backbone, Neck and Head(s) layers, where Input is the image input, Backbone is the image encoded in the form of features, Neck is used to process the feature-encoded image, and Head(s) is the output layer where the model predicts one or more of the outputs.The YOLOv1 model's Backbone layer consists of GoogLeNet network and its architecture is shown in Figure 1.

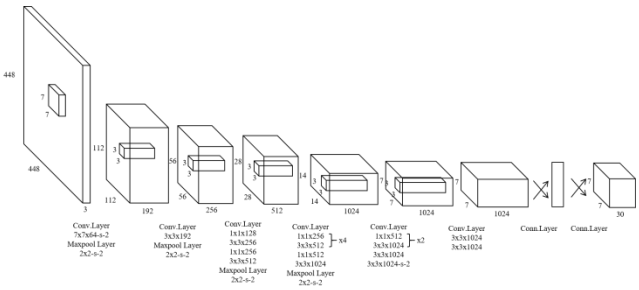

Figure 1. Backbone layer architecture for YOLOv1 model

The YOLOv5 model is different from the v1 model in the BackBone layer and uses a CSPNet network, which reduces the amount of computation and improves the feature representation at the same time through the convolution operation of the segments. The Head part of the output layer outputs the coordinates of the bounding box, the probability distribution of the object category, and the confidence score.YOLOv5 supports multi-scale detection, and usually outputs feature maps at three different scales.By detecting features at different scales (small, medium, and large objects), YOLOv5 is able to adapt to a variety of sizes of objects and improve the accuracy of detection. As shown in Figure 2 YOLOv5s structure, its basic component is Focus, a CBL block consisting of Conv, Bn and

ISSN 0097-996X/25/5603-1610-$1.00 © 2025

Leaky_relu activation function, CSP1_X, CSP2_X and SPP.

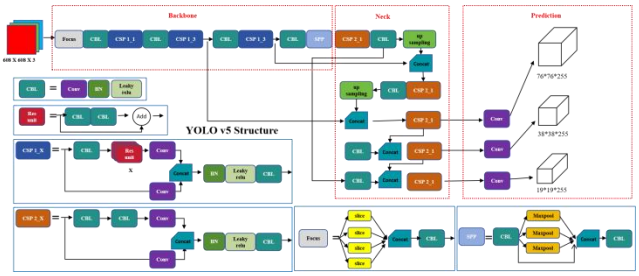

Figure 2. The structure of the YOLOv5 model

Anchor Boxes (Anchor Boxes) are used in YOLOv5 to predict the location and size of objects. The model automatically adjusts the size of the anchor box according to the distribution of the dataset during the training process to improve the detection accuracy. The loss function of the model, Equation (3), consists of Equation (1) localization loss (CIoU), confidence loss, and Equation (2) classification loss.

$$\mathrm{CIoU} = 1 - \mathrm{IoU} + \frac{\rho^2(\mathrm{b}, \mathrm{b}_{gt})}{\mathrm{c}^2} + \alpha v \tag{1}$$

where IoU is the intersection ratio between the predicted and real frames, $\rho^2(b, b_{gt})$ is the distance between the centroids, c is the size of the enclosing frame, v is the difference in aspect ratios, and α is used to balance the various losses.

$$\mathrm{FL}(p_t) = -\alpha_t (1-p_t)^{\gamma} \log(p_t) \tag{2}$$

where p_t is the class probability predicted by the model, α_t is used to control the focus on difficult-to-categorize samples, and γ is a penalty factor, usually set to 2.

$$\text{Total Loss} = \lambda_{box} \cdot \mathrm{CIoU} + \lambda_{cls} \cdot \mathrm{FL}_{cls} + \lambda_{obj} \cdot \mathrm{FL}_{obj} \tag{3}$$

where λ_{box}, λ_{cls}, and λ_{obj} are hyperparameters that regulate the contribution of different losses to the total losses

Contrastive Loss:Contrastive Loss is a loss function for metric learning that aims to train a model so that pairs of similar samples are brought as close as possible in the feature space and pairs of dissimilar samples are moved as far away as possible. The core goal is to learn the similarity and dissimilarity between samples in such a way that similar pairs of samples are mapped to regions close together and dissimilar pairs are mapped to regions far away in the embedding space (typically the feature space of a deep neural network). The contrast loss function improves the feature representation, and by optimizing the contrast loss, the model learns to distinguish more between different classes of features, the mathematical formulation of which is shown in Equation 4.

$$L_{contrastive} = \frac{1}{2N} \sum_{i=1}^{N} \left[y_i \cdot max(0, m - d(x_i, x_j))^2 + (1 - y_i) \cdot d(x_i, x_j)^2 \right] \tag{4}$$

where $d(x_i,x_j)$ is the distance between samples x_i and x_j, usually using the Euclidean distance: $d=||x_i-x_j||^2$,m denotes the minimum distance that needs to be maintained between samples of different categories, y_i is the label, y_i=1 means that the two samples are similar, y_i=0 means that the two samples are not similar, and N is the total number of sample pairs.

3. FBSSDA Attention

FBSSDA (Foreground-Background Same-Scale Difference Attention) attention is a technique inspired by the distinction between foreground and background features in image processing tasks. In order to distinguish between foreground and background features of an image and to obtain features containing significant differences between them, a new FBSSDA attention for extracting the differences between foreground and background features at the same scale of an image is proposed.FBSSDA attention is obtained by letting the weight of the relative values of the background features and the features of the candidate region be added to the object attention score, and then extracting the feature vectors of the foreground and the background regions separately and solving the difference, and obtaining the feature vectors containing significant differences between the two. a feature that contains the significance difference between the two. Such features contain some of the feature space information of the background and affect the subsequent calculation of the object attention score value for that region.

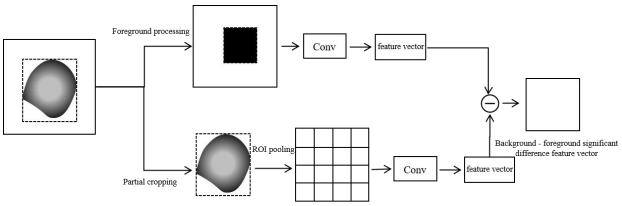

Figure 3. FBSSDA Attention Diagram

The FBDF attention is shown in Figure 3, and its main processing flow is as follows: (i)input the image into the feature extraction network to get the compressed feature map F; (ii)multiply the fixed mask M with the feature map F to get the background feature map Fb=M×F containing only the features of the non-candidate regions; (iii)perform the convolution operation on the background feature map to get the compressed background feature vector α=f(Fb); (iv)crop the candidate region locally from the feature map F and use the region of interest pooling to obtain the local feature map F_f; (v)perform the convolution operation on the local feature map to obtain the compressed local feature vector β=f(Ff); (vi)calculate the significant difference value on the feature vectors obtained from the third and the fifth steps to obtain the feature vector Θ=|α-β| that contains the background-foreground disparity features.

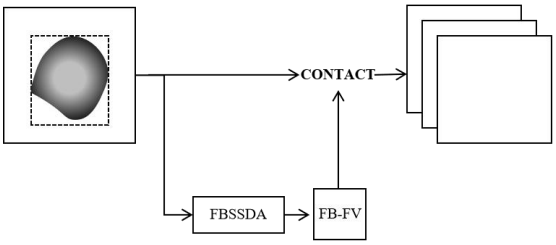

Figure 4. FBSSDA Feature Fusion Module

4. YOLOv5 model based on FBSSDA attention

In order to solve the problem of unknown defects in the production process of industrial panels, we proposed a new attention FBSSDA method and constructed a feature fusion module consisting of FBSSDA attention as shown in Figure 4,

and added this module into the YOLOv5 model to construct an improved YOLOv5 model called FBSSDA-YOLOv5 model. In Figure 4, the FBSSDA attention module outputs feature vectors(FB-FV) of background-foreground disparity features to be fused with the original image to enhance foreground features.

The structure of the FBSSDA-YOLOV5 model is shown in Fig. 5, where the FBSSDA feature fusion module is used to perform feature fusion on the outputs of the Neck layer of the YOLOv5 model for subsequent predictive classification. In order to better learn the differences between similar samples, the contrast loss function is introduced, which makes the object features of the same category more similar and the object features of different categories more different, which can make the unknown defects easier to be detected and defined. After introducing the contrast loss function, the loss function of the FBSSDA-YOLOV5 model is shown in Equation 5.

$$\text{Total Loss} = \lambda_{box} \cdot \text{CIoU} + \lambda_{cls} \cdot \text{L}_{cls} + \lambda_{obj} \cdot \text{L}_{obj} + \lambda_{contrastive} \cdot \text{L}_{contrastive} \quad (5)$$

In display panel defect detection scenarios, there is a common problem of an unbalanced number of categories, which can lead to worse fitting of the already difficult-to-balance multiclassification model. Based on the One-vs-ALL strategy, converting the multicategorization problem into multiple binary classification problems reduces the difficulty of model fitting and allows the model to better distinguish different categories in the feature space, although it brings overhead in computation and storage costs.

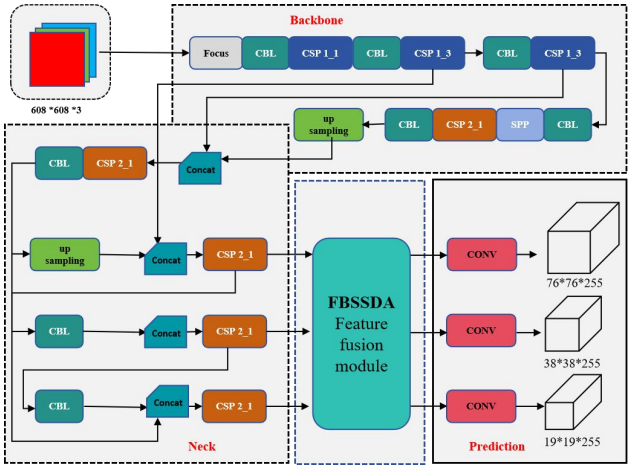

Figure 5. FBSSDA-YOLOv5 model structure diagram

The operation logic of multiclassification to biclassification is shown in Figure 6, and the steps are as follows: (i)input the picture into the network model to get the original output, and the third dimension of the output consists of 4 (box predicted value), 1 (obj predicted value) and N (category predicted value), in which W_i stands for the predicted value of the ith category (non-probability);(ii)calculate the probability of the ith category by taking the maximal value of the other categories as the noni predicted value, denoted as W_J=max(Wp), where $p \neq i$; (iii)use the sigmoid function to convert W_i and W_J into P_i(the probability of category i), where $P_i \in (0,1)$; (iv)repeat steps 2 and 3 to calculate the probability of the other categories and the probability of non-that category; (v)take the probability of the maximum value of all the categories, P_{max}, and the probability of the maximum value of the non-that category, Q_{max}. If $P_{max}>Q_{max}$,the output P_{max} is the final output class confidence. If $P_{max} \leqslant Q_{max}$, the output 1-$Q_{max}$ is the final output class confidence.

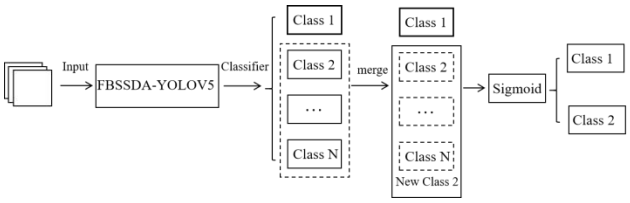

Figure 6. Schematic diagram of the steps for converting a multiclassification to a dichotomous classification

In model forward propagation, since the non-maximal suppression (NMS) algorithm usually relies on a fixed threshold (e.g., IoU threshold) to determine whether to remove redundant frames or not, there exists a significant drawback: it is unable to deal with the unknown defects efficiently, and the detection algorithms are not capable of detecting the features or morphology of defects that have not been learned in the real industrial production. Therefore, the U-NMS algorithm is proposed in the post-processing stage of the algorithm, which improves the NMS algorithm by introducing an uncertainty measure. The steps of the algorithm are (i) to sort all candidate frames based on their confidence scores; (ii) to select the frame Bmax with the highest confidence score as the current frame; (iii) to compute the IoU and uncertainty attenuation between frames, and for each candidate frame B_j overlapping with B_{max}, to decide whether to suppress the frame or not based on its IoU and uncertainty metrics; and (iv) to dynamically through the uncertainty to adjust the IoU threshold; (v) repeat steps (ii) to (iv) until all candidate boxes are processed. In step (ii), IoU attenuation is to calculate the IoU values of the current frame and other candidate frames, and if IoU(B_{max},B_j) is greater than a certain threshold (which can be dynamically adjusted by uncertainty), the attenuation process continues. Uncertainty decay is for each candidate box B_j, calculate its uncertainty difference with the current box Bmax as shown in Equation 6:

$$\text{uncertainty}(B_{\max}, B_j) = \sigma_j - \sigma_{\max} \quad (6)$$

where σ_{max} is the uncertainty measure of the current frame B_{max}. If the uncertainty(B_{max},B_j) of a candidate frame is small, it means that the frame has a high similarity with the current frame, and its confidence can be further adjusted by uncertainty attenuation:

$$\text{score}_j = score_j \cdot \exp(-\frac{IoU(B_{\max}, B_j)^2}{\alpha + \sigma_j^2}) \quad (7)$$

where α is a hyperparameter that controls the degree of combination of IoU and uncertainty decay.

In addition, the predictive logic of the model is also modified and its operational logic is shown in Figure 7 with the steps:(i)input the image, and get the original output after the calculation of the model; (ii)calculate the obj confidence of the current candidate region and the class confidence of each known category, respectively; (iii)judge whether the obj confidence satisfies the threshold condition, and if it does not satisfied, judge that the candidate region is background, if so, go to the next step; (iv)judge whether ClassConfidence satisfies the

threshold condition, if so, judge that the candidate region is a known category defect, if not, go to the next step; (v)extract the probability of not being of that category (background) in step (iv) of the Improvement Point II, calculate the mean squared deviation of the probability values of class confidence and each not being of that category, and calculate the mean squared deviation of the probability values of class confidence and each not being of that category. Class confidence and the maximum of the mean square difference value of each non-that class probability value is the background feature distance; (vi)judge whether the distance obtained in the previous step satisfies the condition, if it does, determine the region as a suspected unknown class defect region and output the prediction result, if it does not satisfy the condition, determine it as a background region.

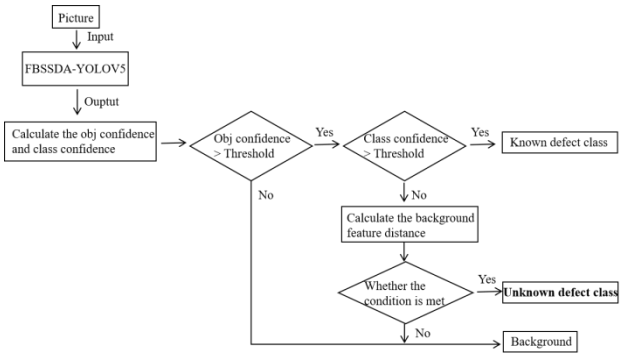

Figure 7. Improving YOLOv5 Network Feature Space and Detection Logic

5. Display panel unknown defect detection and analysis examples

Display panel unknown defect detection process: Unknown defect detection in pictures of display panels, the design of the unknown defect interception algorithm flowchart shown in Figure 8, first from the object detection algorithm to determine a certain class of pictures, to find defective pictures, and the overdetection rate needs to be controlled in a certain range; taking into account the ease of maintenance of the algorithm in the later stages, the algorithm needs to try to cover all the products of all the sites, i.e., a set of parameter adaptation of all the detection; the algorithm needs to be The algorithm needs to re-determine the results of this category of pictures, which accounts for a high percentage, so the reasoning time can not be too long, so as not to affect the operational efficiency.

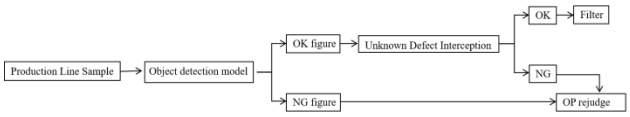

Figure 8. Flowchart of Unknown Defect Interception

Display panel unknown defect detection: In order to validate the accuracy and effectiveness of the algorithm, this paper uses 26309 Mura images provided by the actual production department of the production line for training and testing.The batch of images contains 10 categories of known defects. During the validation process, the batch of images is divided into two parts, 6906 and 19403.To further validate the algorithm's effectiveness in actual production, 42,131 Mura images are specifically collected for inference.

The results detected by the FBSSDA-YOLOv5 model, which introduces the unknown defect interception algorithm in the first part of the pictures, are compared with the original algorithm YOLOv5, and a comparison of the results is shown in Table 1. Among them, 28 pictures were judged as OK by the object detection algorithm, but were detected as NG in the interception algorithm, and the ADC algorithm overdetection was increased from 559 to 1386, an increase of 827 (not confirmed whether it is a personnel omission), indicating that the interception algorithm can effectively reduce the omission, but the overdetection is increased by a larger amount.

Table 1. FBSSDA-YOLOv5 and YOLOv5 detection results

Mura(6906)	FBSSDA-YOLOv5		YOLOv5	
	OK	NG	OK	NG
True-OK	4563	1386	5390	559
True-NG	14	943	42	943

Table 2. Improved FBSSDA-YOLOv5 detection results

Mura(19403)	FBSSDA-YOLOv5		
	OK	NG	UNKNOWN
True-OK	13133	2886	1094
True-NG	10	1846	434

The FBSSDA-YOLOv5 model was further improved by extracting defects with high object scores but low classification scores as unknown defects from the model and verified in the second part of the images, the results of which are shown in Table 2. A total of 10 images were judged as OK by the algorithm, but were manually detected as NG in the second part.The interception algorithm detected 434 defects and overdetected 1,094 (not confirmed in the second part), with an overall manual substitution rate of 67.74% and a missed detection rate of 0.539%.

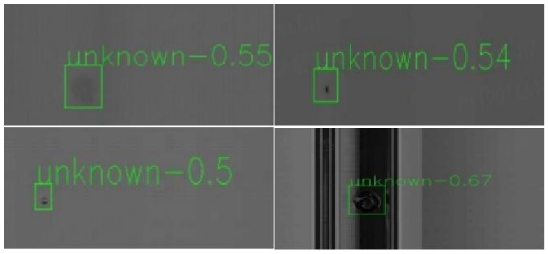

Figure 9. FBSSDA-YOLOv5 modeling of poor interception effect diagrams.

The interception effect of the improved FBSSDA-YOLOV5 model on the provided Mura images is shown in Figure 9. At the same time, the model is also deployed to the production line for defect detection for three consecutive days, and its accuracy is 93.48%, 90%, and 98.51%, respectively, corresponding to the number of detected and real defects of 46/43,30/27,67/66, and the effect of interception of some unknown defects is shown in Figure 10.

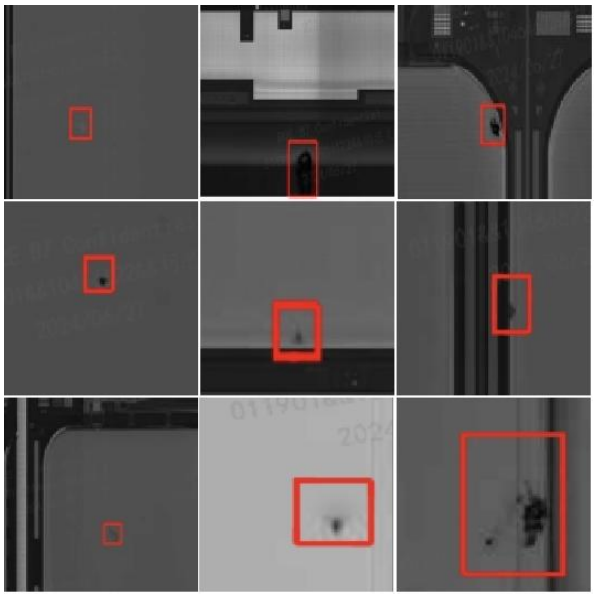

Figure 10. Interception effect of unknown defects on line for FBSSDA-YOLOv5 model.

Finally, the YOLOv5 model was also compared with the FBSSDA-YOLOv5 model 42131 Mura images for practical reasoning, and the comparison of the reasoning results for the OTHER category defects is shown in Table 3.The FBSSDA-YOLOv5 model shows an improvement in the detection of the OTHER category defects in the metrics of mAP-50, which suggests that the model can significantly increase the number of unknown defect identification and improve the confidence level of defects, and the proposed model has a very obvious improvement in the accuracy and recall of OTHER category defects.

Table 3. Results of mAP comparison between YOLOv5 and FBSSDA-YOLOv5 model for OTHER category defects

	Presion	Recall	mAP-50	mAP-95
YOLOv5	0.906	0.829	0.896	0.775
FBSSDA-YOLOv5	0.922	0.843	0.905	0.777

6. Conclusion

Aiming at the problem that the YOLO-based model algorithm cannot effectively recognize the unknown defects leading to missed detection in the actual defect detection scenarios of display panels, a defect detection method based on the improved YOLOv5 model with FBSSDA attention fusion is proposed to solve the problem of unknown category defect detection in panels. The method has the following characteristics:

1. FBSSDA attention is proposed to increase the weight of background-foreground differences. This method can enhance the extraction ability of the foreground-background difference features, which makes the feature display of defects more obvious.
2. The FBSSDA-YOLOv5 model is proposed, where foreground and background difference features are extracted by FBSSDA attention, and a contrast loss function is added to expand the differences between different defect categories during training. Then for category discrimination, the multicategorization is converted to dichotomous classification, i.e., known defects and unknown defects, based on the One-vs-ALL strategy. In the post-processing session, U-NMS is used to compensate for the disadvantage that NMS cannot detect unknown defects, and the prediction logic is updated. This method is more capable of detecting unknown defects than the original YOLOv5 model, and is now used in the production of display panel processes.

The improved YOLOv5 method based on FBSSDA attentional fusion used in the defect detection process can also be widely applied to the process production of other display panels and also to other industrial.

7. References

1. He, F., Tan, J., Wang, W., Liu, S., Zhu, Y., & Liu, Z. (2023). EFFNet: Element-wise feature fusion network for defect detection of display panels. Signal Processing: Image Communication, 119, 117043.
2. Redmon, J. (2016). You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition.
3. Almufareh, M. F., Imran, M., Khan, A., Humayun, M., & Asim, M. (2024). Automated brain tumor segmentation and classification in MRI using YOLO-based Deep Learning. IEEE Access.
4. Benjumea, A., Teeti, I., Cuzzolin, F., & Bradley, A. (2021). YOLO-Z: Improving small object detection in YOLOv5 for autonomous vehicles. arXiv preprint arXiv:2112.11798.
5. Pham, D. L., & Chang, T. W. (2023). A YOLO-based real-time packaging defect detection system. Procedia Computer Science, 217, 886-894.