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YOLOV8X-HICAUPS: AN ATTENTION BASED APPROACH FOR ACCURATE PCB DEFECT DETECTION

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Abstract— **Existing PCB inspection methods are becoming outdated due to their limitations in detecting errors. Computer vision technology offers a more effective, automated solution for maintaining PCB quality by improving problem area identification. In this paper, we introduce YOLOv8x-HICAUps (YOLOv8x-HorNet-CBAM-Attention based Up-sampling), an innovative method for PCB defect detection that enhances earlier developments while tackling significant challenges in practical applications. The imperfections in the surface of Printed Circuit Boards (PCBs) during the production negatively impact product quality, directly affecting the stability and dependability of devices. Precisely identifying small flaws on the compact PCB surface amidst intricate backgrounds continues to be a major challenge. Earlier models showed encouraging outcomes but continue to encounter limitations, such as insufficient real-world validation, elevated computational expenses for training, and an emphasis on identifying only minor flaws, which limits their adaptability. YOLOv8x-HICAUps includes multiple crucial innovations to tackle these difficulties, featuring the use of the HorNet backbone, CBAM-driven attention mechanisms, attention based up-sampling, and enhanced detection heads. The HorNet backbone is optimized to capture intricate features from high-density PCB designs and improves the capacity to identify even tiniest flaws. The integration of CBAM will improve spatial and channel attention so that defects like "mouse bites" and "spur" can be accurately identified in intricate PCB environments. Attention-based Up-sampling promotes better preservation of defect characteristics, preventing blurriness and improving overall detection precision. Finally, the simple design of the detection head stresses small-object detection, improving efficiency for immediate deployment on embedded systems. Harmonizing a lightweight design with exceptional accuracy, YOLOv8x-HICAUps is fine-tuned for resource-limited settings and has enhanced generalizability and effectiveness in practical PCB manufacturing situations. Extensive tests on PCB defect datasets confirm the capabilities of YOLOv8x-HICAUps, demonstrating superior detection accuracy of 98.3% and reliability in comparison to current models, thereby establishing it as a valuable resource for practical PCB quality assessment.**

Keywords— **PCB defect detection, Deep learning (DL), YOLOv8x, small-object detection, Defect Classification, Machine vision.**

I. INTRODUCTION

Identifying the problem area is important for maintaining the quality of Printed Circuit Boards [1]. With the advancement in Computer Vision technology, conventional inspection techniques have proven inadequate with respect to the scope of error-prone actions and are gradually being substituted with automated techniques. This includes classical techniques like thresholding, edge detection, and localization techniques, as well as ML and DL techniques [2].

Among these techniques, Automatic Optical Inspection (AOI) has emerged as one of the most commonly employed techniques for identifying PCB defects, resulting in notable enhancements in precision and Effectiveness. The development of Electronic Information sector [3] and the progress of present and future Information Technology [4] have promoted the continuous growth of demand for PCB products and brought new challenges to PCB manufacturing. The current trends in PCB manufacturing support higher reliability, higher quality, and smaller sizes, making defect detection important. These advances have brought significant challenges to the defect detection system in PCBs using Machine Vision.

The PCB production is a complex process and it often creates various defects, with some minor defects, such as open circuit, short circuit, and spur will have adverse effects on the consistency of PCB component functionality, which poses difficulties for the model to effectively detect various flaws and exactly at that same instant.

Because of the variation in production processes, the number of Defects on PCB surfaces usually sums to less than 4500 pixels, and the measurement of spurs typically remains at less than 300 pixels, which accounts for only 0.005% to 0.07% of detailed images, which have about 6500000 pixels resolution [6]. Hence, its relatively challenging to obtain rapid and precise analysis for small-scale defects. Recently, many concepts integrating Machine vision and Deep learning concepts have widely been used to detect defects in PCBs as they can learn independently and replace tasks with knowledge-centric projects [5], [6]. PCB is not defined in the network structures using DL [7], which can be mainly divided into the classification process, product identification process and distribution partner [2]. In particular, the object detection-based algorithm usually has two levels of detection. Algorithms that generate regional proposals to identify objects for recognition purposes like Faster R-CNN and single-level search algorithms, which are known for their fast capabilities by simultaneously providing the product distribution and location information. For example, Hu and Wang [8] demonstrated the accuracy of the small PCB problem using Faster R-CNN with ResNet50 as a simple model design, (MobileNet-YOLO-Fast) has compact size and impressive instantaneous efficiency. Lee et al [10] combined Hybrid-YOLOv2 and Faster R-CNN (FRRF) design to accurately identify the double-in-line package (DIP) soldering issues in PCBs. YOLO-HMC [11], is an improvised method for surface defect detection in PCBs, has a temporal architecture but the quality is slightly lower for defect detection. The mentioned algorithm has achieved very powerful detection. However, the problem of precise and instant identification of small differences between complex PCBs by adjusting the density and sample rate has not been fully solved. The feature engineering features of YOLOv8x are specially improved and optimized. The results of the project include,

1) This project presents a new model with YOLO-HorNet-CBAM-AUps (YOLOv8x-HICAUps) framework based on the YOLOv8x development, which improves the lightweight of the model while improving the accuracy, efficiency and rapid development.

2) The Backbone architecture uses the HorNet model to improve resource cleanup and data interoperability. The enhanced Convolutional Block Attention Module (CBAM) is designed to improve the ability of the network to extract features (such as short circuit and open circuit) from the complex backgrounds of PCB substrates which has similar colors and look.

3) The up-sampling process is treated as operational up-sampling (AUps), so that the entire PCB image content semantic information can be quickly and accurately detected for thick targeted PCB defects on the surface in a wide receptive field. AUps achieves a better balance between performance, accuracy and design, by eliminating the merging burden while keeping the content sufficient to utilize the ability of small DH to identify small problems and complete heavy models simultaneously.

The Printed Circuit Board defect detection process is detailed in Section II, and the YOLOv8x-HICAUps model is detailed in Section III. By its following Section, the experiment and results of the proposed solution is implemented on publicly available data.

II. RELATED WORKS

A. Vision-Based Methods used in PCB Defect Detection

Detecting surface defects on PCBs is essential for ensuring the quality and reliability of the modern electronic devices. Over the years, several strategies for automating and improving flaw identification have been presented. These approaches can be divided into the following categories: The traditional method of PCB defect detection relies on manual inspection that is both time-consuming, error-prone, and not scalable for industrial manufacturing. AOI was based on an improvement over the principle of optical-based defect detection but suffered issues about robustness, generalization, and cost that most smaller enterprises could not afford. Some techniques employed for image processing were threshold segmentation [12], edge detection, segmentation methods [13], Support Vector Machines [14], and Backpropagation Neural Networks [15] as typical algorithms of machine learning. Those techniques, however, did suffer problems with image alignment and referencing. Deep learning has now changed the game in the detection of PCB defects. It is showing outstanding improvements in accuracy, robustness, and scalability.

Region proposal-based two-stage detectors such as Faster R-CNN [8] are highly accurate but very expensive in terms of computations and slow. One stage detectors like YOLO series [9] are fast and accurate. In comparison with other concepts and algorithms, both accuracy and the detection speed are higher [16]. In the advancement of YOLOv4, GsIoU [17] is used for better box regression, while in the advancement of YOLOv5, new data augmentation methods are incorporated to improve inference speed. The other is SSD or Single Shot Multibox Detector [18], which focuses on real-time detection and tends not to perform as efficiently in detecting small objects in complex backgrounds. A new lightweight defect detection scenario was introduced, YOLOX [19], using DL techniques. It is a small-scale network that does not require any intervention. YOLOX integrates an enhanced version of CSPDarknet and incorporates the Coordinate Attention mechanism [CA], remarkably improving the ability of the model to detect small defects on PCB surfaces. The CA mechanism especially focuses on enhancing spatial and channel interrelationships between feature maps, hence allowing the network to effectively improve and identify fine defects that might be lost on standard detection models. Another alternative was presented by Liu et al [17], who used YOLOv4 as the base model of their study. The new box regression loss function they have developed is called Gaussian Intersection-over-Union (GsIoU), that is focused on maximizing the precision of bounding box prediction. GsIoU assesses the prediction box coherently at all possible anchor points, thus providing it with more flexibility to adjust according to the change in shape and size of objects. The accuracy of the final box regression is improved by this, especially when objects to be detected are small or have variability in shape, increasing the effectiveness of the whole defect detection system.

B. YOLO-Based PCB Defect Methods

Advances within the model of YOLOv5, together with all its models in the family of YOLO models, provide attention mechanisms like CA and CBAM. These significantly boost the model's ability to focus on subtle and complex defects. The mentioned techniques enable the model to give attention to important areas of the image; consequently, detection accuracy, particularly for minor defects, significantly increases, such as micro scratches, open circuits, and unwanted copper. For industrial defect detection purposes, YOLOv5 has improved both the inference speed and the precision using multiscale detection techniques and data augmentation strategies. These techniques, Coordinate Attention and the Convolutional Block Attention Module (CBAM) [20], were added to variants YOLOX [19] and YOLO-MBBi [21] for better detection of tiny defects. YOLO-MBBi [21], is an enhanced version of YOLOv5 for defect detection in PCBs, which incorporates MBConvolution, CBAM, Bi-directional Feature Pyramid Network, Depth-wise convolutions, and the SIoU loss function to improve detection accuracy and efficiency, achieving superior performance compared to existing methods in terms of precision and computational efficiency. Improvements in the detection of PCB defects have been achieved using advanced techniques, including [22] YOLOv5, CBAM, CARAFE, and attention-based Up-sampling. Real-time processing, something really important in an industry where efficiency and speed really matter—is achieved along with improvements in detection accuracy, especially for smaller and intricate defects. PCB-CFR [6] integrates Coordinate Feature Refinement (CFR), CARAFE Up-sampler, additional detection layers, and advanced attention mechanisms to enhance multi-scale feature fusion, improve tiny defect detection, and achieve real-time performance in defect detection applications in PCBs of YOLOv6[23], a single stage object detection framework specifically designed to address industrial application challenges. It focuses on improving detection accuracy and inference speed while maintaining computational efficiency. YOLOv7[24] a groundbreaking improvement in real-time object detection that leverages innovative "bag-of-freebies" techniques. These techniques enhance model training without adding inference cost, achieving state of art performance in both speed and accuracy.

The use of HorNet in YOLOv8x_HICAUps model could provide comparable accuracy to PCB-YOLO with reduced computational overhead and attention-based Up-sampling likely provides better feature enhancement compared to PCB-YOLO's anchor box strategy, especially for irregularly shaped small defects. the model YOLOv8x_HICAUps focuses on modern, efficient components (HorNet, CBAM, attention-based Up-sampling), making it more lightweight and adaptable than PCB-YOLO. While PCB-YOLO [25] has been fine-tuned for PCB defect detection with specific improvements like UAM and EIoU, the YOLOv8x_HICAUps model's design offers competitive advantages in handling small objects, resource efficiency, and flexibility for advanced datasets like HRIPCB.

YOLO-HMC [11], an Improvised Method for Surface Defect Detection in PCBs. Introduces several key improvements to improve the accuracy of the detection and efficiency for tiny PCB defects in complex backgrounds. The HorNet structure improves the ability of feature extraction, especially for tiny defects in dense and complex PCB layouts. It enhances the anti-interference ability of the model by providing richer semantic information for feature extraction and improving the ability to highlight locations of defects in highly similar PCB backgrounds. This ensures better localization of defects, especially for defects with subtle differences in shape or color from the background, and replaces the traditional Up-sampling layer with the CARAFE module, which aggregates contextual semantic information within a large receptive field. It reduces information loss during feature processing and improves the clarity of defect boundaries.

Although YOLO-HMC might enhance the detection of defects, it has very poor precision when it comes to fine-grained PCB defects as features are not fully refined. In contrast, YOLOv8x-HICAUps utilizes HorNet and CBAM, which reach a higher level of precision and recall, mainly in small categories of defects like 'spur' and 'mouse bite'.

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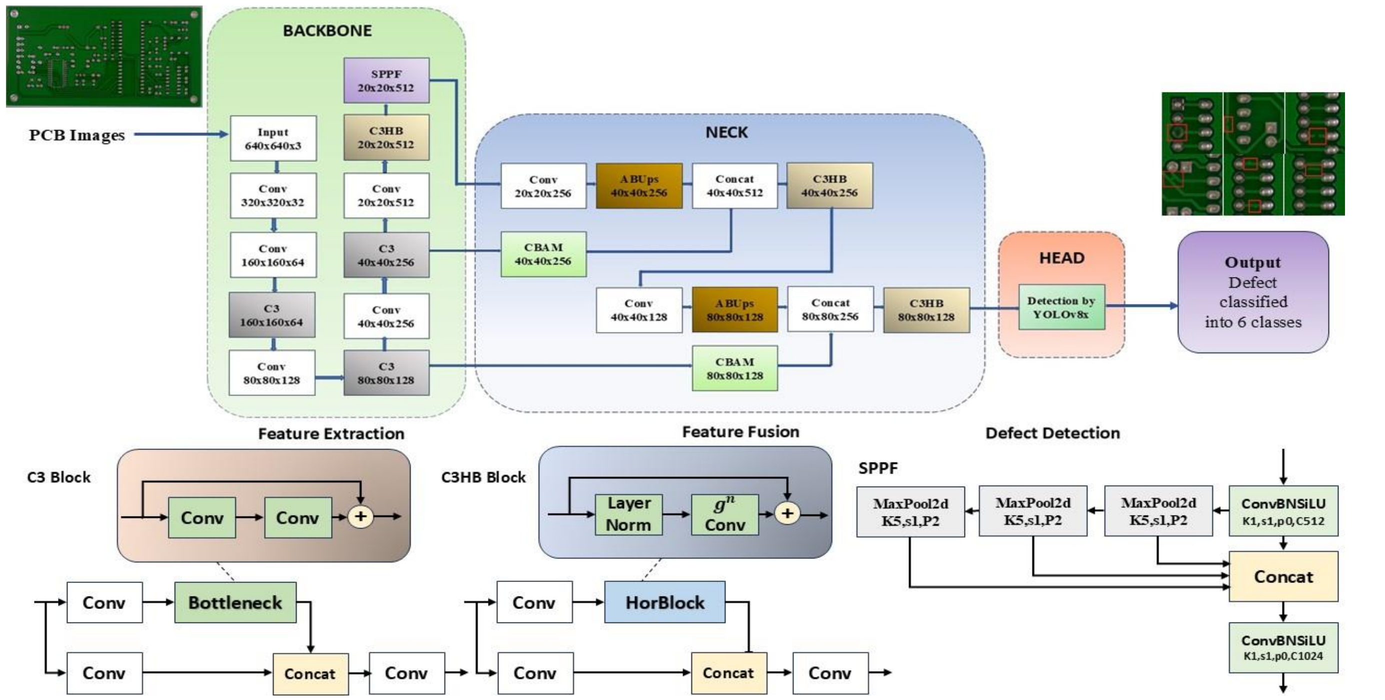

Figure 1 Overall Workflow of YOLOv8x_HICAUps

YOLOv8x is a recent release of the YOLO series, thus representing an extremely advanced algorithm for object detection regarding improved precision and speed. The customized HorNet [11],[26] backbone uses channel and spatial attention modules applied through CBAM and efficient feature fusion modules for C3 and C3HB. The backbone includes the Spatial-Pyramid Pooling Fusion to capture multiscale spatial information. The Up-sampling layer (attention-based Up-sampling [27]) also comprises an attention-based module that preserves spatial features while increasing the resolution. The presence of these modules enables the model to draw out and fine-tune features at different scales. This allows YOLOv8x to be used more efficiently in real-time detection scenarios, especially in complex environments with objects of varying sizes. It makes the model achieve better precision and robustness and suitable for various applications like object detection, segmentation, and classification.

III. METHODOLOGY

Object detection tasks in industrial settings are unique, especially when dealing with PCB defects. Unlike natural image detection tasks, PCB defect detection involves identifying minuscule [1] and often indistinguishable targets against a densely packed background. These targets are frequently tiny-sized pads, vias, or traces, which exhibit minimal contrast with their surroundings, leading to significant challenges such as false positives, missed detections, and low precision. This has led to the necessity to improve the detection architecture with specific needs for PCB defect detection [6].

YOLOv8x_HICAUps is an advanced detection framework that extends the YOLOv8 model by including sophisticated modules like HorNet, CBAM (Convolutional Block Attention Module), and attention-based Up-sampling. These modules are specifically introduced to improve feature extraction, fusion, and representation while detecting small targets in complex environments for PCB images.

The proposed scheme is tested using ordinarily image processing. From the simulation of the experiment results, we can draw to the conclusion that this method is robust to many kinds of watermark images.

A. Overall Framework of YOLOv8x-HICAUps

As shown in Figure 1, we design a novel YOLOv8x_HICAUps framework based on improved

YOLOv8, which consists of the backbone part for feature extraction, the neck part for feature fusion and the Detection Head part for final recognition results. Owing a significant quantity of small-size pads, vias, and compact traces being spread across the PCB substrate, this leads to some interference with the precise extraction of essential defect characteristics of the framework. This issue is frequently addressed by enhancing the channel and spatial focus of the model, Zheng et al [28], incorporated the Co ordinate Attention (CoordAtt) module and HorBlock module to the network to improve the characteristics of feature extraction procedure in the channel domain and spatial domain, diminish the ailing characteristics, and understand the intricate context. According to the YOLOv7 architecture developed by Chen et al. [29], creating spatial features in the frequency domain via global filtering of HorBlock improved the precision of the algorithm on the dataset for finding defects. In order to tackle these challenges, the suggested YOLO CBAM-HorNet framework integrates various novel alterations to the conventional YOLOv8 structure. These adjustments aim to enhance feature extraction, attention mechanisms, and feature integration to increase the identification of small PCB defects while preserving computational efficiency. The foundation of the proposed framework leverages the HorNet module, which executes recursive gated convolutions via the C3HB module. Unlike traditional convolutional modules, the C3HB [26] setup enhances direct spatial interactions both before and after the feature extraction stage. This design ensures that the extracted feature maps are enriched with semantic information, improving the ability of the model to distinguish defects from the complex PCB backdrop. In addition to semantic enhancement, the C3HB module includes convolutions lightweight depth-wise separable (DWConv) to reduce computational requirements while preserving the integrity of crucial features. This technique is particularly skilled at handling small targets tightly clustered in the image, enabling the system to capture high-quality features without interference from irrelevant components. The neck of the YOLOv8 model is crucial for combining spatial location information from shallow layers with the semantic information obtained from deep layers. However, the primary neck module has difficulty effectively aiming at the small faulty areas, especially against the complex PCB backdrop where the characteristics of defects are often hidden by adjacent components. The neck region includes CBAM (Convolutional Block Attention Module) to tackle this problem. The CBAM enhances the network's ability to discriminate by focusing selectively on important feature channels and spatial regions [20]. Unlike other attention mechanisms, the CBAM employs both channel and spatial attentions to emphasize important features and reduce background noise. This combined attention method is highly effective for spotting small flaws that may be overlooked in a larger setting. However, the typical module for the CBAM often relies solely on the maximum response values throughout the complete feature map, potentially missing several defect targets in one image. To overcome this limitation, we present an adapted CBAM module that partitions the feature map into subspaces, ensuring that within each subspace, all defect features are significantly highlighted. This modification enables the model to efficiently handle multi-target detection situations, ensuring that all characteristics related to defects are preserved for later processing. Feature fusion [30] using CBAM in the neck is crucial for synthesizing multi-scale information from different levels of the network. The Up-sampling part of the original YOLOv8 design uses simple methods like Nearest-neighbor interpolation, which often miss deep semantic details and do not effectively enhance feature information. This constraint becomes especially difficult when detecting minor flaws, as their features may be further diminished during the Up sampling process. To tackle this issue, we incorporate an attention-based Up-sampling module into the neck. This module generates context-aware Up-sampling kernels that consider both local and global traits, ensuring that significant defect-specific details are preserved throughout the fusion process. By combining spatial and semantic data through attention-guided reconstruction, this element greatly enhances the receptive field and produces more detailed feature representations. As a result, the model achieves enhanced detection capabilities for minor defects while maintaining the richness of semantic features. The YOLOv8 detection head recognizes objects at different scales. In the original design, three detection heads were developed to recognize large, medium, and small items. Although this design is effective for identifying natural images, it proves to be less efficient for detecting PCB defects because most targets are quite small. The large and medium sized detection heads decrease the feature maps to a point where small flaws are lowered to subpixel levels, leading to significant information loss. This extreme compression adversely affects the model's detection precision, especially for small and tightly grouped defect targets. In this case, we improve the detection head by keeping the small objects detection head only. This is carefully adjusted to detect very small imperfections. Eliminating the large and medium detection heads along with their feature pyramid structures stops the needless compression of defect features. Concentrated design facilitates a singular emphasis on enhancing the thorough collection of semantic and spatial information in small targets, guaranteeing accurate detection and reducing false negatives. While the original YOLOv8 backbone excels in general object detection, it struggles with the intricate features of PCB defects. To enhance feature extraction, we integrate the HorNet backbone, which comprises the C3HB module and recursive gated convolutions. These lightweight convolutional methods efficiently capture high-level semantic features while minimizing computational expenses. The HorNet backbone significantly improves the ability of the model to differentiate between regions that are free of defects and those that contain them, even in crowded real time PCB images.

B. Description of the Improvements

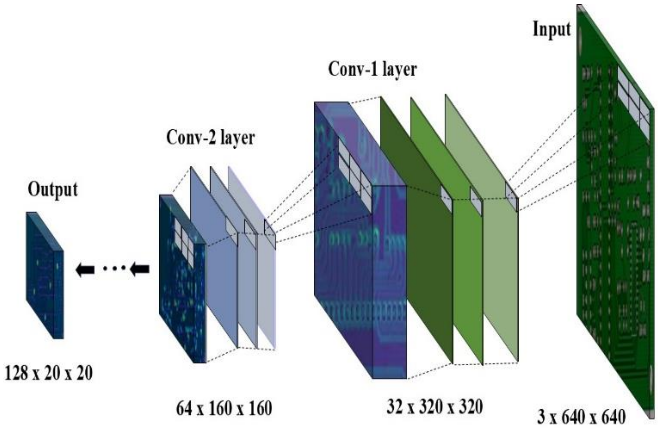

Figure 2 Down-Sampling Process

1) HorNet based Feature Extraction Technique: In the case of defect detection on PCBs, there exists a high occurrence of defect-free components, and the target area for detection in most cases contains minimal contrast as compared to its background. In this case, it becomes quite challenging to obtain features since this leads to interference in the acquired data, reducing the efficiency in defect identification.

Densely packed components are observable in detection images, as shown in Figure 2. The channel dimension (C) increases while the feature map dimensions (H×W) decrease as we extract more information from these images. The size of the convolution filters in the feature extraction process remains roughly constant with this reduction to maintain a constant receptive field in the network model. Convolution kernels subsequently incorporate large areas of such flawless structures surrounding the defect regions to the convolution process. Such flawless structures interfere with the extraction of the features since they are often similar and packed highly, which complicates the task of the convolution network in detecting the defects accurately. We recommend the application of the C3HB module in an attempt to correct the feature extraction capability of the model. In contrast to the C3 module, the HorNet design, that is based on lightweight convolution operations, is incorporated into the C3HB. To get comparable results, HorNet's depth-wise separable convolution (DWConv) only requires one-third of the calculations required for traditional convolution [26].

As displayed in Figure 3, as the input P_0 is fed into HorNet, it expands the dimension by using the Convolution approach and then splits it into two groups of feature maps P_1 and Q_0 based on a predefined ratio. Following the completion of

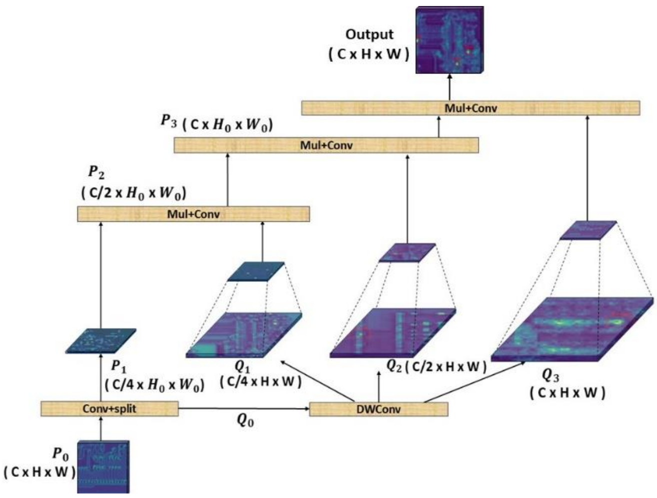

Figure 3 HorNet Process

DWConv, Q_0 gives various sub-feature map outputs Q_i ($1 \leq i \leq \alpha$). Subsequently, P_1 and Q_1 perform the dot product operation together with convolution and increase the dimension to achieve P_2. Continue the iteration process until reaching the final sub-feature maps Q_α.

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By connecting feature information through the different information exchanges described above, the HorNet generates self-weighted parameters that allow the network model to achieve high-order deep characteristics with more robust semantic data, effectively improving the network's clarity. The following equation represents the HorNet process assuming the input as $x \in R^{H\times W\times C}$ Where f stands for convolution operation, φ for depth-wise separable convolution, and α for the spatial order established during HorNet's operation.

$$P_0 = f(x) \tag{1}$$

$$C_0 = \frac{C}{2^{\alpha-1}} \tag{2}$$

$$\varphi\,(Q_0) = [\,Q_1^{H\times W\times C_0}, Q_2^{H\times W\times 2C_0}, \ldots, Q_\alpha^{H\times W\times C}\,] \tag{3}$$

$$P_i = \begin{cases} P_0^{H\times W\times C_0}, & i = 1 \\ f(P_{i-1} \odot Q_{i-1}) & i \geq 2 \end{cases} \tag{4}$$

2) CBAM-Based Attention Mechanism: For object identification methods, it is quite challenging to separate faulty locations from the intricate backdrop of PCB pictures. Our work addresses this by incorporating the Convolutional Block Attention Module (CBAM) into the YOLOv8 architecture's neck and backbone components.

As shown in Figure 4, CBAM incorporates channel attention and spatial attention sequentially to suppress distracting background noise and let the model focus on key elements. This double attention method significantly helps the model to detect very minute defects in densely placed PCB layouts. By combining spatial and channel attention [31], CBAM effectively emphasizes faulty traits at many levels, in contrast to conventional attention mechanisms like SENet [32], which solely focus on channel-wise properties. This skill is particularly useful for detecting PCB defects, since these defects are typically small and difficult to notice.

Despite numerous studies exploring enhanced attention mechanisms like MCBAM [11], which divides feature maps into subspaces for targeted attention, MCBAM can occasionally unduly emphasize particular regions, leading to the missed detection of smaller or subtler defects. In contrast, CBAM places a balanced focus on both global and local traits, providing robust and flexible enhancement of features without introducing additional computational complexity.

The CBAM module operates in two stages:

Channel Attention: Aggregates spatial information through average pooling and max pooling, followed by a shared MLP:

$$Mc\,(F) = \sigma\,(W1\,(\,\delta\,(\,W_0\,(\,AvgPool\,(F)))) + W1\,(\,\delta\,(\,W_0\,(\,MaxPool\,(F))))) \tag{5}$$

where F is the input feature map, δ is the ReLU activation, W_0 and W_1 are MLP weights, and σ is the sigmoid function.

Spatial Attention: Aggregates channel information using average pooling and max pooling:

$$Ms\,(F') = \sigma\,(\,f^{7\times7}\,([\,AvgPool\,(F');\ MaxPool\,(F')\,])) \tag{6}$$

where $f^{7\times7}$ is a convolutional function with a 7×7 kernel. By sequentially applying M_c and M_s, CBAM adaptively enhances relevant features while addressing limitations such as overemphasis on maximum responses, which can arise in more complex attention modules. This design ensures robust performance for detecting multiple tiny defects in PCBs.

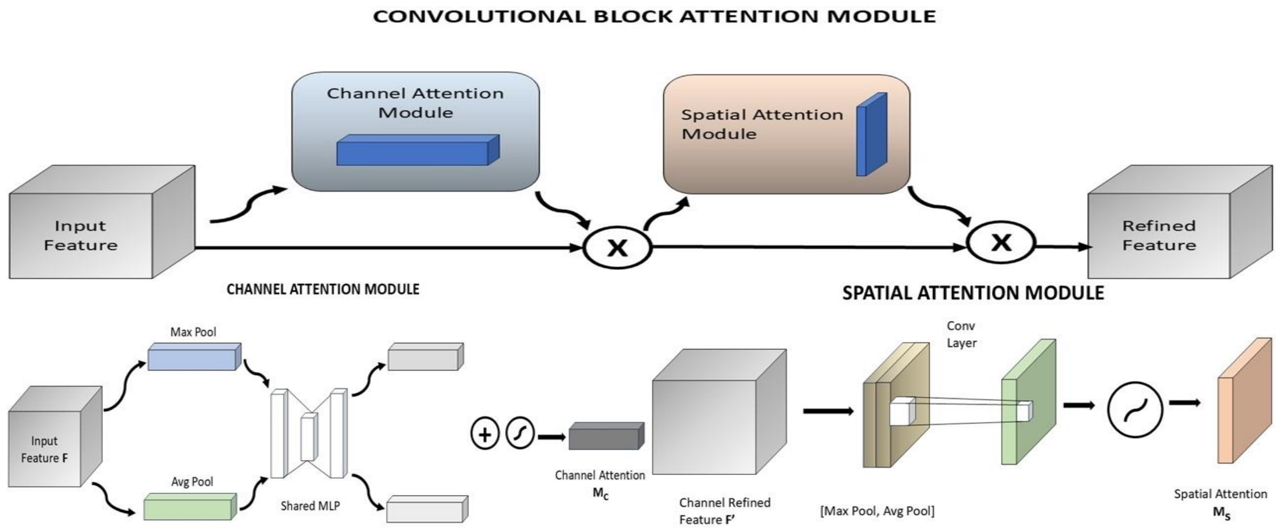

Figure 4 Basic Process of CBAM

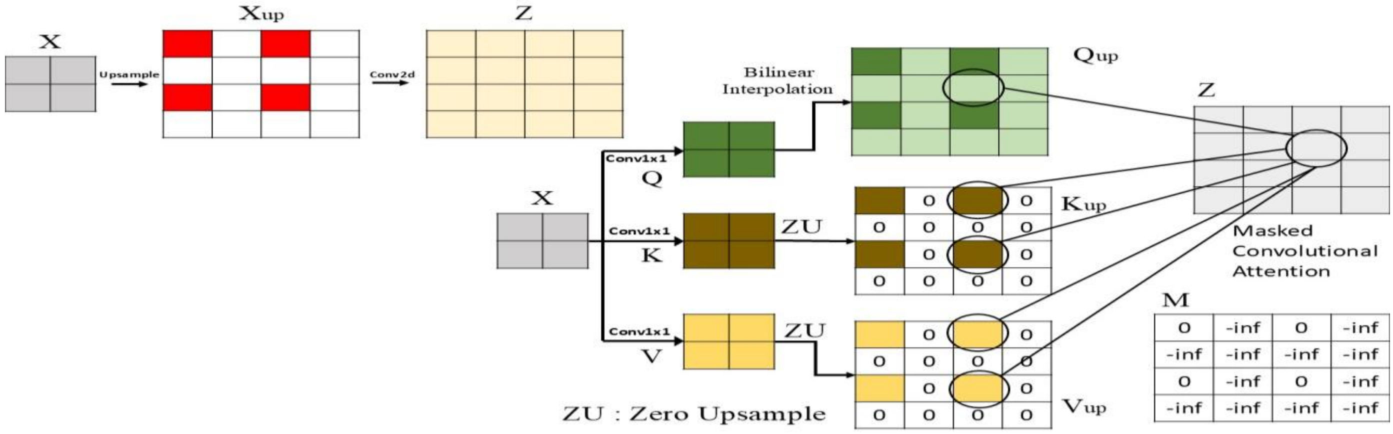

Figure 5 Attention Based Up-sampling Mechanism

3) Attention Based Up-sampling Mechanism: In this study, we employ an Attention-based Up-sampling (AUPS) technique to improve feature reconstruction [27]. Although conventional techniques such as nearest-neighbor Up-sampling or transposed convolution are useful, they frequently struggle to gather enough context from surrounding pixels. This may result in artifacts like hazy transitions or patchy color changes, especially in activities needing high spatial precision, like PCB defect identification. CARAFE (Content-Aware ReAssembly of Features) [22] has surfaced as a formidable solution to these problems by utilizing an expanded receptive field and dynamic kernel forecasting to enable context-sensitive feature reconstruction. Nevertheless, CARAFE adds extra computational intricacy and design limitations, rendering it less suitable for certain lightweight models and real-time uses. Rather than using CARAFE, we utilize a more effective attention-based Up-sampling method. This technique attains better reconstruction by directly representing the spatial connections and smoothness between neighboring pixels. AUps finds a balance between computational efficiency and reconstruction quality as shown in Figure 5, retaining enough contextual details while avoiding the overhead linked with approaches such as CARAFE.

4) DH Optimization Technique for Minimal PCB Defect: In current studies, small targets are generally characterized by either their comparatively small physical dimensions in reality or as items that take up less than 32×32 pixels within a picture [33]. Based on the PCB dataset examined in [34], several defect targets are actually lower than 10×10 pixels, as emphasized in Table I. These small defect targets frequently lack essential information during feature extraction because of their restricted dimensions, posing a considerable challenge in defect detection activities. YOLOv8x, an enhanced iteration of YOLO, includes several detection heads (DHs) to tackle objects of different scales. In the original YOLO design, DHs relate to down-sampling factors of 8x, 16x, and 32x, intended for identifying small, medium, and large items, respectively. Although this multi-scale detection system guarantees strong performance for various object sizes, the PCB defect detection task mainly focuses on small targets that represent an insignificant percentage of the total image. For example, using an input image dimension of 640×640, the picture is minimized to just 20×20 pixels following the 32x down-sampling DH process. This intense compression causes various small and medium-sized defect targets to be reduced to less than one pixel, resulting in considerable loss of semantic and positional data. Thus, employing all three DHs as done in the original YOLOv5 or YOLOv8[35][36] models is not ideal for detecting small objects in the PCB defect area.

To overcome this limitation, we enhance the YOLOv8x detection head design for small defect detection by eliminating the medium and large object DHs. This method guarantees that the feature extraction process focuses on retaining intricate details essential for identifying small PCB defects. Our comparative experiments, demonstrated in Figure 8, confirm this optimization. The findings indicate that keeping just the small-object DH greatly enhances detection precision. By tailoring YOLOv8x's detection heads to the requirements of PCB defect detection, we achieve enhanced accuracy and efficiency. A detailed discussion of these results is provided in Section IV.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. Dataset

The Experimental setup is shown in Table 1. Illustrated in

Configuration	Type
Operating System	Windows 11
CPU	Intel Xeon
Memory	12 GB RAM
GPU	NVIDIA Tesla T4
Graphic Memory	16 GB
CUDA	12.1

Table 1 Experimental setup

Figure 6, the dataset employed in the public dataset HRIPCB [37] published by the experiment Peking University, featuring 693 pictures and six flaws with 2777×2188 average pixels. By the ratio of 9:1 the train and test data is split and worked according to it.

B. Model Evaluation Indicators

Object detection differs from classification; in classification, it is essential to identify where the predicted bounding box is located, and each image in object detection may include various types of objects. Consequently, mean Average Precision (mAP) is utilized in this study. mAP denotes the average value of defect average precision (AP). The formula for calculation is outlined below. While the recall indicates the amount of missed detection, the precision clearly shows how accurate the detections are.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{7}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{8}$$

$$\text{AP} = \int_0^1 P(R)dR = \sum_{k=1}^{N} P(K)\Delta R(K) \tag{9}$$

$$\text{mAP} = \frac{\sum_{i=0}^{n} AP(i)}{n} \tag{10}$$

Letters TP, FP, and FN stand for True Positive, False Positive, and False Negative.

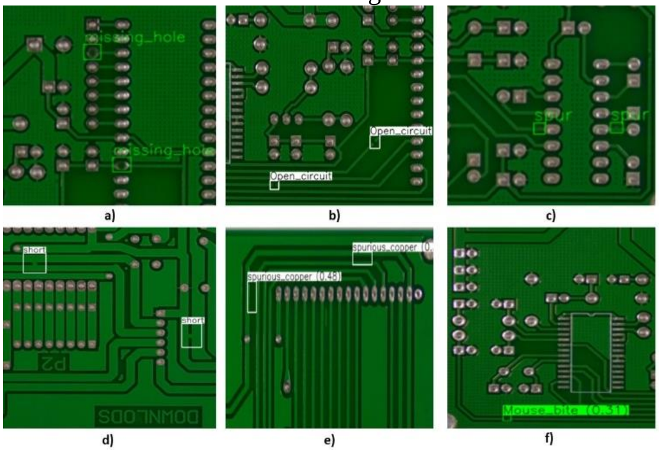

Figure 6 HRIPCB dataset defect diagram: (a) missing hole; (b) open circuit; (c) spur; (d) short; (e) spurious copper; and (f) mouse bite.

C. Result Analysis

The HRIPCB dataset was used to train the YOLOv8x-HICAUps model, which convergence reached at epoch 100. Obviously, the box loss, classification loss, and DFL loss have significantly decreased and stabilized after epoch 50 as shown in Figure 7. Visual depictions of loss metrics clearly show that both training and validation losses are persistently decreasing without signs of overfitting, which illustrates that the conclusion of learning processes has been successfully completed. At 50 and 100 epochs, precision, recall, and mAP became stabilized at that stage, the precision was 0.9786, recall was 0.9784, mAP@0.5 was 0.983, and mAP@0.5:0.95 was 0.537. These trends reveal that optimal performance in defect detection in PCBs is achieved through the model's strong generalization ability as well. Detection of every subcategory of the defect in YOLOv8x-HICAUps was highly impressive. For instance, the fragile subcategory Missing hole has been rated with a precision of 0.987, a recall of 1, and mAP@0.5 of 0.994. The remaining defective subcategories that are of lesser importance include Mouse bite, Open circuit, and Spurious copper. Each of them recorded high precision rates combined with impressive recall rates, having their respective mAP@0.5 values of 0.970, 0.982, and 0.990 as shown in Table 2. The model shows high and consistent precision for complex defects, such as Spur and Short, which vary widely in size and nature, making it a reliable option for

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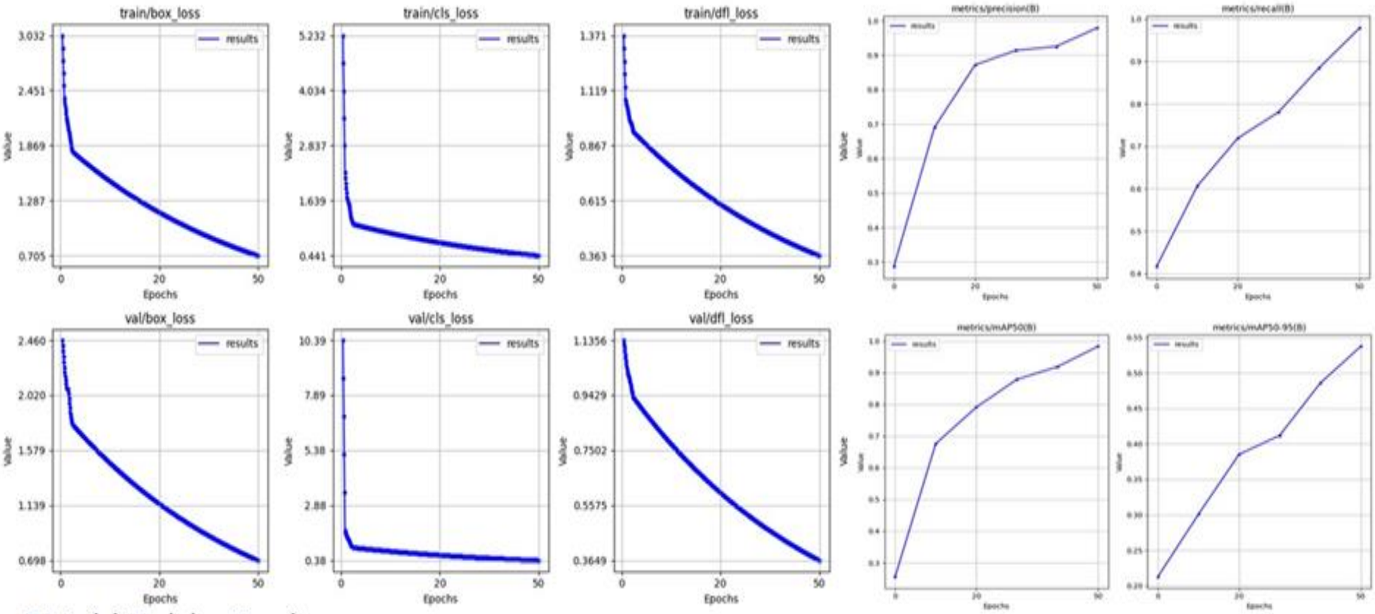

Figure 7 Model Training Results

Defect Type	mAP@0.5 (%)	mAP@0.5:0.95 (%)
Missing Hole	99.4	64.2
Open Circuit	98.2	56.4
Spur	97.3	43.3
Short Circuit	99.1	57.8
Spurious Copper	99.0	53.7
Mouse Bite	97.0	52.0

Table 2 Values of Defects detecting PCB faults.

In comparison with other models like YOLOv7, YOLOv8, and Faster R-CNN as shown in Figure 8, the results obtained from YOLOv8x-HICAUps are better in all the essential metrics, namely mAP@0.5 and mAP@0.5:0.95. Although false positives have hampered Faster R-CNN and YOLOv8 and YOLOv7 had missed detections of certain types of defects, the YOLOv8x-HICAUps has significantly outperformed them in accuracy, precision, and reliability, which substantially mitigated these drawbacks. Visual representations of loss and other related metrics also support these results. The training and validation loss metrics that show a steady decrease along with the stable performance metrics like precision, recall, and mAP@0.5 indicate that YOLOv8x-HICAUps is successful in both learning and detection accuracy. It is, however found to be in trend across all epochs without any signs of overfitting, thus proving to be robust and versatile for practical applications in defect detection. YOLAv8x-HICAUps provided HorNet, CBAM, and attention-based Up-sampling techniques for better feature extraction and detection. It highly decreased the number of model parameters; therefore, the convergence of training phase got accelerated without significantly increasing the total computational cost. This approach makes it suitable for many resource-constrained industrial systems. Based on this, the YOLOv8x-HICAUps model stands out. It has practical use in real settings because the high accuracy, recall, and mAP lead to a marked aspect of fast convergence with the possibility of the presence of several types of defects. The model is,

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therefore, an error-free model in PCB defect detection not only based on advanced methodologies and operational effectiveness but also in showing signs of establishing a new standard concerning reliability and efficiency in industrial defect identification.

A prominent characteristic of the model is the employment of the HorNet backbone that has been fine-tuned for the identification of complex features within PCB layouts to detect minuscule flaws such as "mouse bites" and "spur." This enhanced backbone enhances feature extraction, which in turn enables the model to recognize defects that would be difficult to identify in the conventional models. The CBAM improves the model using spatial and channel attention to increase the accuracy in defect location detection. This process is in step with YOLO-HMC's [11] HorNet and using attention mechanisms so that it functions more efficiently over complex PCB background where defects would be hard to distinguish from substrates. The attention-based up-sampling mechanism in YOLOv8x-HICAUps ensures semantic coherence at every step of the up-sampling process. This confirms that important defect features, such as small holes or fine lines, are preserved during feature scaling, avoiding the loss of critical details often encountered with simpler interpolation methods. By focusing on specific features relevant to defect detection, the attention-based up-sampling method enhances feature reconstruction and leads to more accurate and accurate detection results. This further enhances the model by adding C3 layers, SPPF (Spatial Pyramid Pooling Fast), and C3H components. These enrichments serve to add depth and flexibility in the model can better detect defects at different Scales. The detection head streamlined for detecting small objects confirms that even the smallest defects are detected with great efficiency, thereby making YOLOv8x-HICAUps a reliable choice for real-time execution on embedded devices. All these developments together make YOLOv8x-HICAUps extremely effective, accurate, and versatile for practical PCB defect identification tasks.

Figure 8 Comparison with different Models

V. CONCLUSION

This paper introduced a new approach using YOLOv8x for HICAUps (HorNet Integrated with CBAM and Attention-based Up-sampling) in order to enhance the prediction and identification of complex causal connections and uplifting trends in complex datasets. The task is challenging because of the different types of data patterns that require unique detection criteria and often intricate relationships among features that hide the existence of subtle patterns.

To overcome these challenges, the YOLOv8x framework was augmented with advanced attention mechanisms like CBAM and AUps, which further improved its responsiveness to the critical spatial and causal data. Such improvement further enables the model to better detect minor patterns and predict causal uplift across various settings and thus further enhance its real-time functionality. Comparative tests have demonstrated that the enhanced model successfully detects and predicts complex patterns with superior accuracy of 98.3%. Even with the good performance of the model, the existing validation is based primarily on public domain datasets, and the data available is still limited in scope.

Therefore, an in-depth understanding of various data trends and causal relationships will be achieved through additional data collection and refinement. The model will update frequently in the future with real-world datasets and few-shot learning methods to adjust to scenarios with scarce labelled data. This would not only make the model more resilient but also increase its usability in industrial predictive systems and causal evaluation, thus further solidifying its position in real-time, large-scale data settings.

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