Automatic detection of solar cell surface defects in electroluminescence images based on YOLOv8 algorithm

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Article Info

ABSTRACT

In the last few years, the development of renewable energies has increased on a large scale. At least, to guarantee the security and stability of the photovolataic system's production, it is imperative that the photovoltaic modules exhibit a high level of reliability. Therefore, the development of an intelligent detection environment to enable the identification of defects in solar cells during manufacturing has become an important issue for the growth of the photovoltaic (PV) sector. This work proposed a fault diagnosis of surface solar cells using deep learning methods for computer vision, using the eighth version of the you only look once (YOLOv8) algorithm. This detection method was applied to a dataset of electroluminescence (EL) images containing twelve PV cell defects on a publicly available heterogeneous background. Then, using this dataset, we trained, validated, and tested the YOLOv8, YOLOv5 models. The results show that YOLOv8 provides a high level of accuracy in fault diagnosis compared with YOLOv5, and also improves the detection speed of the model. Indeed, the average precision achieves 90.5% This suggested approach ensures high accuracy in fault identification which demonstrates the effectiveness of computer vision to identify multi-object cell defects.

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1. INTRODUCTION

Renewable energy sources such as solar will play an increasingly critical role in future energy systems with rapid cost reductions and high availability [1]. Photovoltaic (PV) power plants make efficient use solar cell energy, facilitate grid management and improve the quality of electricity [2]. PV power plants are composed of several PV panels, whose reliability is essential for the stability and safety of the system. Many factors, such as solar cell manufacturing defects, have an impact on these modules' efficiency.

One of the main sources of PV module failure during PV system operation is the verification of the production quality of the solar cells. In factories, this control is performed by humans using electroluminescent (EL) image capture machines [3]; this causes errors while evaluating the production quality of these solar cells. Therefore, it has become crucial for the expansion of the PV industry to perform intelligent testing for these solar cells' flaws and thus develop an intelligent detection environment. Intelligent detecting defects in solar cells is very important to ensure that these defective cells do not progress to the next step in the production chain. Cracks, fingers, short circuits, and printing faults with intricate interferences in the backdrop are some

of the most common manufacturing flaws on the cells that are currently recognized. Indeed, PV cells are susceptible to hot spots and short circuits while in use [4]. An EL image's surface has a complex random texture backdrop, and the closeness between the background and defect edges makes it difficult to extract defect features [3]. The same goes for the line-like crack, and star-like crack defects, which are similar and sometimes overlap, which makes manual detection of defects in EL images complicated. In the literature, we can find basic methods to detect surface defects on solar cells, such as [5] which uses fourier image reconstruction, [6] used electronic speckle interference (ESPI). Then, the potential introduction of artificial intelligence (AI) in the energy sector has given a new alternative to solve the problems of solar cell fault detection. In fact, some works have proposed various methods of machine learning to resolve the problem of classification and detection fault; [7]–[9] have used machine learning and ensemble methods for the detection of different solar panel defects by electrical measurement, [10] they used deep neural networks and infrared images to detect a fault on the surface, [11]–[13] they used convolutional neural network (CNN) to detect hotspot. Du et al. [14] use CNN with 3 branches based on the transfer learning strategy to identify PV cell faults using eddy current thermography, Korkmaz and Acikgoz [15] have also used the multi-scale CNN and the transfer-learning technique to detect 11 different PV module flaws. Chen et al. [16] proposed a fault diagnosis method that can determine the time and location of a fault occurrence in real time and with accuracy using a hybrid diagnostic engine.

In recent years, the two-step algorithm has been improved, [17] proposed fast regional convolutional neural network (RCNN), by reducing the spatial pyramid pooling layer and thus imcresing the detection rate of RCNN, subsequently, a new two-stage detector light-head RCNN was proposed by Li et al. [18] in an attempt to speed up detection and simplify the network. Nevertheless, the fully connected layer of the conventional CNN model has a very large number of neurons, as well as the number of training parameters, and the ability to make generalizations is low, which is not recommended for real-time detection. As one-step neural network, the you-only look-once (YOLO) algorithm outperforms the RCNN in terms of real-time detection speed; in fact, YOLO treats the entire image in one pass, making it faster and more efficient. Yin et al. [19] they introduce lightweight YOLO for fault detection, and [2] they have used residual network (ResNet) and methods to identify PV cells faults.

YOLOv8 is the most recent version of YOLO that has surpassed all existing object detectors in terms of velocity and accuracy (accuracy of 56.8 mAP) [20]. In this research, the YOLOv8 algorithm was adopted for the diagnosis of solar cell surface defaults and applied to the photovoltaic electroluminescence dataset (PVED) to detect twelve types of defaults namely: scratches, cracks (line and star), printing errors, finger interruptions, thick lines, fragments, corners, horizontal dislocations, vertical dislocations, black cores, and short circuit defects, with 90.5% mean average precision compared to YOLOv5 detection algorithms; apart from enhancing diagnostic accuracy, the speed of pattern detection is significantly improved. As best we can tell, this is the first research to examine how the YOLOv8 algorithm can be used to detect surface defects on PV modules during factory production; the main contribution of this study is propose an improved approach to solar cell surface faults detection on YOLOv8.

Using the suggested YOLOv8-based method, the accuracy of solar cell manufacturing flaw detection will be increased. The new technique has a number of benefits that will be helpful for learning and identifying the distinct traits of various flaws (12 defects have been highlighted), which may be challenging to identify using conventional methods.

Real-time object detection is made possible via the YOLOv8 algorithm, which is renowned for its quickness. As a result, the suggested method is ideally suited for industrial applications, where precise defect detection is crucial for producing high-quality solar panels. The suggested solution can be more affordable than conventional defect detection techniques since it can be adopted with simple hardware equipements, eliminating the requirement for conventional, unreliable faults detection techniques.

The dataset presents a diverse range of defects, 12 defects were highlighted. Our deep learning model collects essential data from large data sets to produce accurate predictions and reduce over-fitting. The other sections are organized as follows. In section 2 we expose the related work, and illustrates, specifies the detection framework of this paper YOLOv8 and YOLOv5, we introduce also the dataset ans instrument. Section 3 is devoted to presenting the results and engaging in detailed discussion, and section 4 concludes this article.

2.   METHOD

This section of the paper provides an overview of the methodology employed in our research project. In order to identify and classify solar cell surface defects, we have chosen to use state-of-the-art computer vision techniques. More specifically, our approach involves the use of the YOLOv8 algorithms, which have demonstrated outstanding performance in object detection tasks; we will conduct a comparative analysis with YOLOv5. To ensure transparency and facilitate a thorough understanding of our research methodology, we will devote a significant part of this section to a detailed description of the experimental procedures

implemented throughout this study. This will include a meticulous description of each step, from data collection to training and model evaluation. In addition, before that, we will present a comprehensive literature review. This review will serve to highlight existing research and knowledge in the field of solar cell fault detection.

2.1. Literature review

Many research studies on EL image defect detection focus on image classification or object detection: Akram *et al.* [21] suggest a classification by neural network architecture CNN using just four convolutional layers. Additionally, they apply data augmentation to increase the network's robustness and reduce the size of the input image to save processing time. Tang *et al*. [22] have considered four classes of fault are seen to be the best solutions for categorizing flaws, and generative adversarial network (GAN) are utilized to produce a large enough database of photos and improve classification accuracy. Similarly, this classification technique has been used for fault detection in photovoltaic installations based on thermography and electroluminescence PV images. In wor [12], [13] to find hotspots, they used CNN, [14], [15], [23] utilize multi-scale and transfer learning techniques CNN.

To increase the detection precision and location accuracy of solar cells surface defects, faster-RNN, efficientNet, and autoencoder are three deep learning technologies that [23] perfectly combine to create an end-to-end deep learning pipeline, that locates and segments anomalies at the cell level of PV modules using EL images. Zhang *et al*. [24] developed a detection technique that integrates the output of faster RCNN, and RFCN. Recently, the use of novel object detection methods based on YOLO algorithms has drawn the attention of researchers, integrating visible and infrared images, applied YOLOv5 algorithm to detect module defects of PV plants [2], utilize YOLOv7 to diagnose photovoltaic modules faults in real-time [25], and in [25] they develop a YOLO-PV technique to detect defects in solar cell surfaces.

Existing techniques have greatly shortened inspection times, but they still fall short of the requirements for inspection and the real-time processing of EL pictures. In some contexts, with high real-time requirements and delicate material resources, it is still challenging to apply. In addition, a significant number of false detections brought on by low accuracy substantially impair the dependability of the algorithms, and call for additional study and applications of new and recent algorithms like YOLOv8 to resolve this problem.

2.2. YOLOv5 algorithms

YOLO is an algorithm that integrates the best features of ResNet, denseNet, and feature pyramid networks (FPN) to provide real-time object recognition [2]; The YOLO method uses CNNs to detect objects, the algorithm only needs one forward propagation through a neural network to do so. This means that the algorithm is run only once to make a prediction on the entire image as shown in Figure 1.

YOLOv5, was published in February 2020; first backbone pulls the features from the CNN-generated input image, and the neck then controls the feature regression for the bounding box. The bounding box is then extended by the prediction portion. The predicted bounding boxes are then non-maximally suppressed (NMS) for 1-2 milliseconds for each image by YOLOv5 [26].
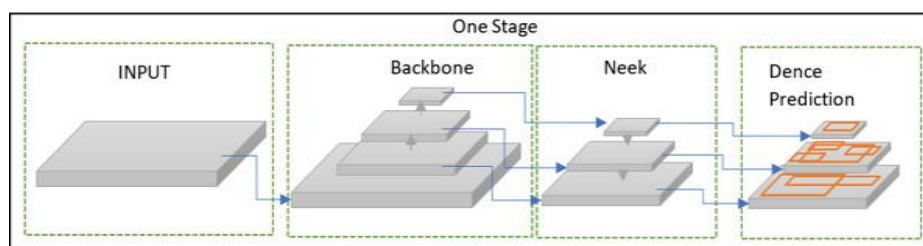

Figure 1. One stage detector architecture

Dimension clusters are used as anchor boxes in the YOLOv5 algorithm to anticipate bounding boxes. The network predicts four coordinates for each bounding box, tx, ty, tw, and th [2], as shown in Figure 2. When the bounding box prior has dimensions width and height, p_w, p_h, and the cell is offset from the image's top left corner by (cx, cy), the predictions match according to [27]:

$$b_x = (2.\sigma(t_x) - 0.5) + C_x \tag{1}$$

$$b_y = \left(2.\sigma(t_y) - 0.5\right) + C_y \tag{2}$$

$$b_w = p_w \cdot (2. \sigma(t_w))^2 \tag{3}$$

$$b_w = p_w \cdot (2. \sigma(t_w))^2 \tag{4}$$

2.3. YOLOv8 algorithms

The YOLOv8, is the latest version of the YOLO system developed by Ultralytics [20]. Until now, there is no article about YOLOv8 architecture; only some differences between YOLOv8 architecture and YOLOv5 architecture are listed by [20]: replace the C3 module with the C2f module, replace the first 6×6 convolution (Conv) with 3×3 convolution in the Backbone, delete two convolutions layer (N°10 and N°14 in the YOLOv5 config), replace the first 1×1 convolution with 3×3 Conv in the Bottleneck, and use decoupled head and delete the objectness branch [20]. The module C2f is summarized in the diagram as shown in Figure 3, where "f" represents the number of features, "e" represents the rate of expansion, and CBS is a block made up of a Convolution, a BatchNorm, and a sigmoid linear unit (SiLU) later [28]. All of the bottleneck's outputs are concatenated in C2f. C3 solely utilized the output of the previous bottleneck. Figure 4 provides a visual diagrammes summarizing of YOLOv8 module [29].
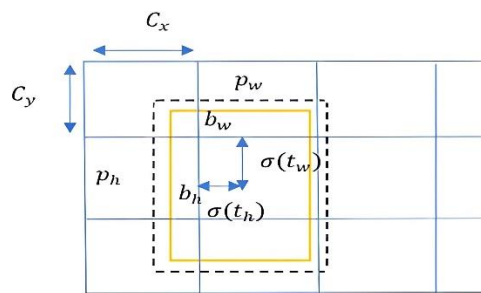

Figure 2. Bounding boxes with position prediction and dimension priors
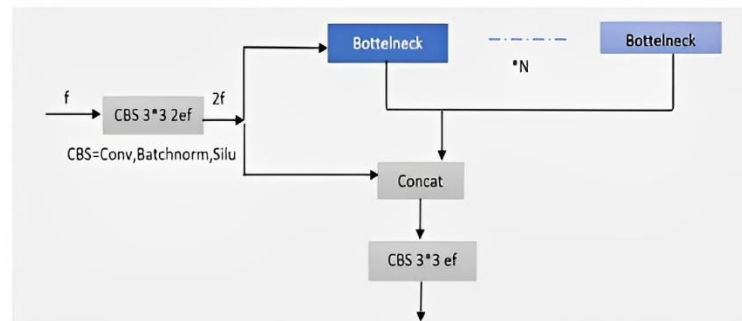

Figure 3. Yolov8 C2f module [29]

There are five scale variants have been made available by YOLOv8: YOLOv8n (nano), YOLOv8s (small), YOLOv8m (medium), YOLOv8l (large), and YOLOv8x (extra large). It can be launched using the command line interface (CLI) or deployed as a PIP package. Additionally, it offers numerous integrations for deployment, training, and labeling. We can adjust the models to find any fault in solar cells through transfer learning.

YOLOv8 is anchor-free, which lowers the number of box forecasts and accelerates the non-maximum impression (NMS) [29]. Additionally, when traninig YOLOv8 employs mosaic augmentation, but it is disabled during the last ten epochs due to research showing that using this augmentation throughout the whole training period can be harmful [30]. In the whole YOLO series, YOLOv8 managed to strike the perfect balance between detection speed and detection effect. YOLOv8x achieved an AP of 53.9 evaluated on the MS COCO test-dev 2017 dataset for an image size of 640 pixels (compared with 50.7 for YOLOv5 with the same image size) [29].
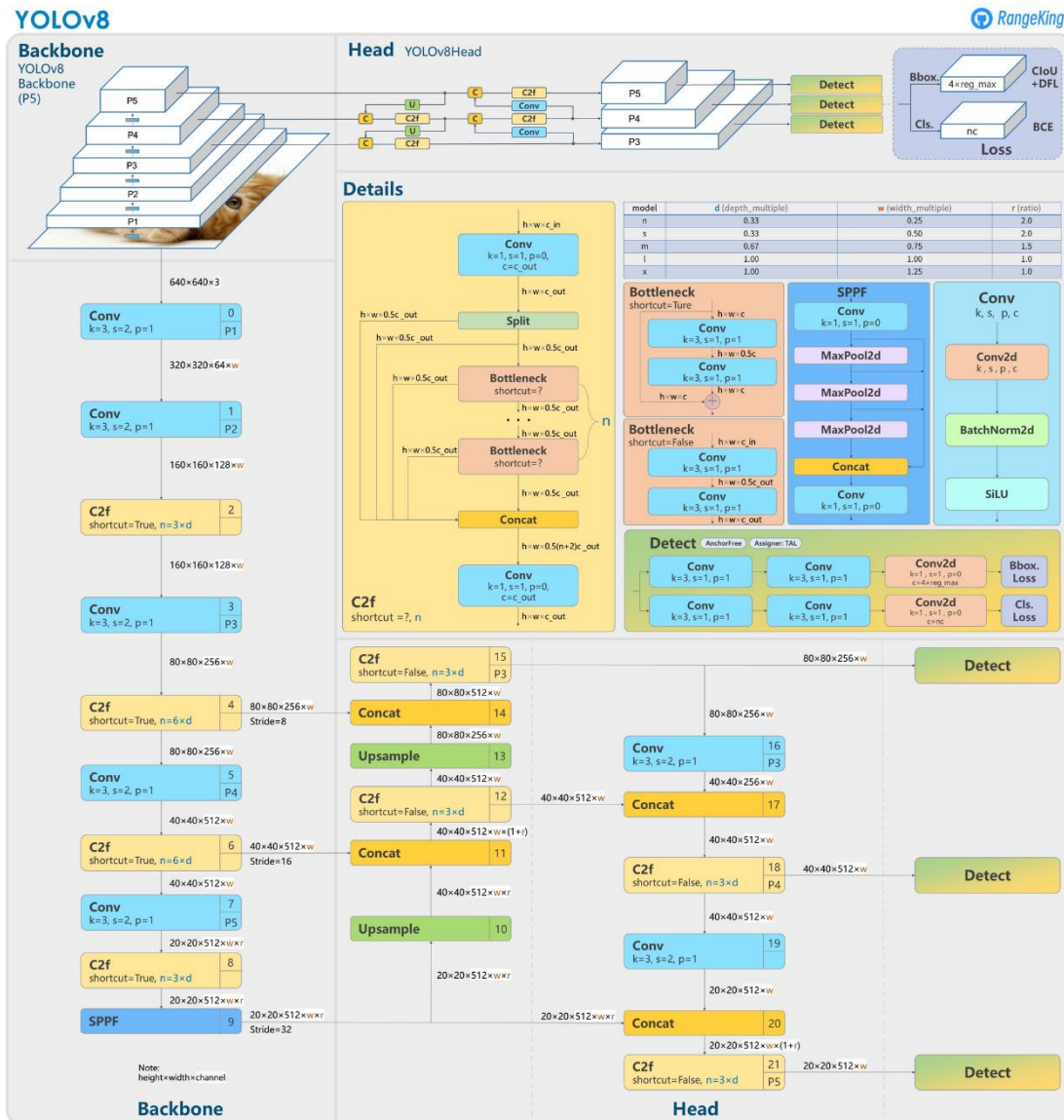
Figure 4. YOLOv8 module [29]

2.4. Proposed method

The methodology adopted in our work is the use of the detection model YOLOv8; which avoids the need of a local suggestion network and enables fast and precise detection of objects. The algorithm is tweaked to increase detection accuracy by reducing the number of parameters required. We have utilized computer vision algorithm to automatically identify faults in EL images while manufacturing solar modules. The process is broken down into a number of phases, as seen in Figure 5.

First, data collection has been done, this phase consists in collecting a large dataset of surface images of photovoltaic modules during their manufacture in factories, in our case the images of photovoltaic cell defects were collected from the global public dataset of EL images published by the Hebei University of Technology and Beijing University of Aeronautics and Astronautics [30]. We need to check that there are no duplicates and that the labeling has been done correctly. It is important to make sure that the data set is balanced.

Then, preparation of the data; the dataset of 12 surface defects is prepared for training and testing the smart faults detection system. This consistes labeling the images with boundingboxes all over the faults in a surface cell, which is done in the case of our data set. The data that has been labled are then devide into training, validation, and testing sets, to make sure both are representative of the full set of data. It could also be essential to perform other pre-processing processes, including shrinking or standardizing the data.

After that, agorithm selection, the appropriate object detection algorithm is chosen to train the defect surface cell detection model. There are a number of algorithms, each with unique advantages and disadvantages, including YOLOv8, YOLOv5, YOLOv7, and RCNN. Depending on the needs of the intelligent defect detection system, the algorithm chosen must perform well on all the data collected and be capable of handling a variety of defects. Because of its efficiency and speed, YOLOv8 is a very popular option, but other algorithms can also be used depending on the situation. We have also worked on the YOLOv5 algorithm in order to make a performance comparison with YOLOv8.

Model training is then conducted; in which the two models YOLOv8 and YOLOv5 are trained on the previously prepared labeled dataset. Model training consists of training the model using deep learning to identify the image features of the various defects on the surface and locate them accurately. The two models are developed using a deep learning framework, such TensorFlow or PyTorch, which gives users the resources they need to create and develop neural networks.

Finally, evaluation of modele. We use multiple metrics, such as accuracy, recall, precision, and F1 score, to assess the effectiveness of the trained model. These measures give an indication of how accurately the model distinguishes between different faults. If the model's performance is unsatisfactory, it is possible to modify the hyperparameters or add training data to improve them (data augmentations).
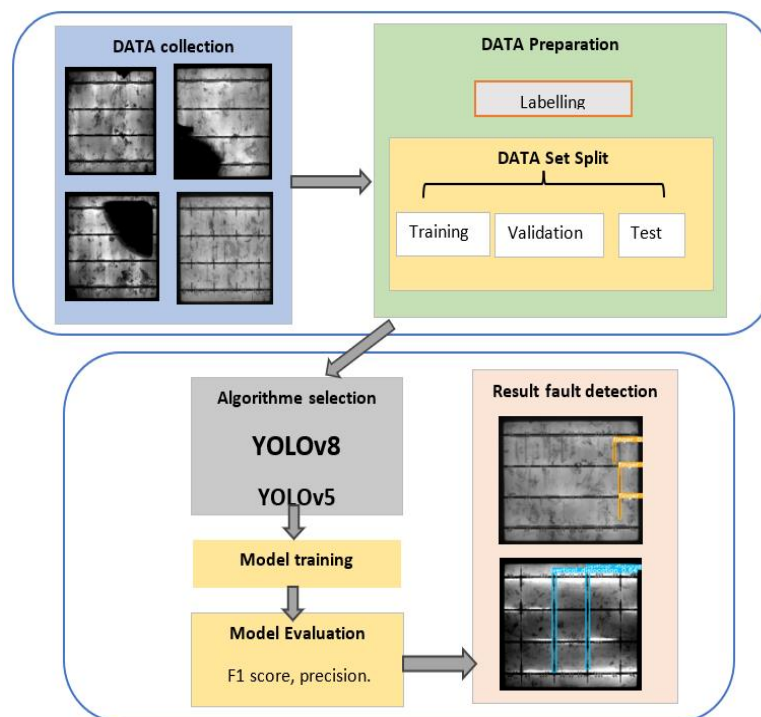

Figure 5. Proposed method

2.5. Data set and metrics

As part of this study, a sample of high-resolution images of PV cell defects was collected from the global public dataset of EL images that the Hebei University of Technology and Beijing University of Aeronautics and Astronautics jointly published [30]. This collection data set had anomalies with a higher resolution, greater variety, and greater completeness, contains 12 various aberrant flaws, including cracks (line and star), black cores, finger interruptions, thick lines, scratches, fragments, corners, printing errors, horizontal dislocations, vertical dislocations, and short circuit defects. The flaws in the data set are depicted in Figure 6.

Figure 7 shows the distribution of the twelve defect types in train and validation data set [30]. On the basis of the distribution of the defect categories, an imbalance in the number of samples between the different types can be noted initially, with significant variations (38% for finger fault, 0.11 for corner fault). So, we have chosen to use data augmentation techniques and category weighting strategies to address these challenges effectively. This approach aims to correct sample distribution disparities and maximize the usefulness of the limited datasetThe training set consists of 80% of the EL images, while the validation and test sets are made up of the remaining 20%.
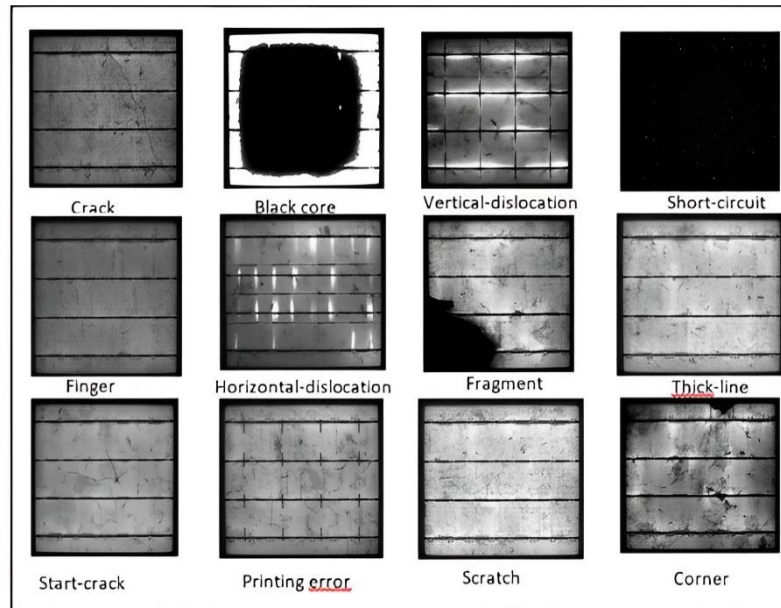
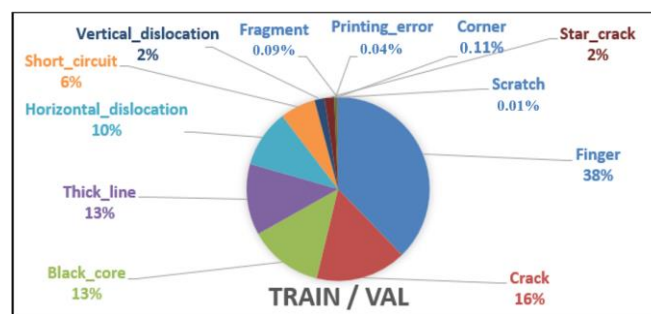Figure 6. Original solar cell defect types

Figure 7. The distribution of 12 defect categories

One often used metric in object detection is intersection over union (IoU), the detection is deemed successful when the IoU exceeds a predetermined threshold. It refers to the intersection ratio between the ground truth and the bounding box predicted by the model, which is given as:

$$IoU = \frac{X \cap Y}{X \cup Y} \tag{5}$$

where, X represents the bounding box's area, and Y is the ground truth that the model predicts.

Precision (P), Recall (R), and mean average precision (mAP) are metrics commonly used to evaluate and compare the model's performance. TP and TN are respectively the numbers of true positives and true negatives, and FP and FN are the numbers of false positives and false negatives, respectively. A measurement called precision is calculated as the ratio of true positives to all positive results.

This formula is used to compute it:

$$Precision = \frac{Tp}{Tp + Fp} \tag{6}$$

The proportion of correctly identified positives (true positives) to all positives is known as the recall metric. It is computed using the following formula:

$$Recall = \frac{Tp}{Tp + Fn} \tag{7}$$

The AP represents the area under precision-recall curve. Finding the AP for each class and then the average across all classes yields the mean average precision (mAP):

$$mAP = \frac{1}{N}\sum_{i=1}^{N} APi \qquad (8)$$

3. RESULTS AND DISCUSSION

The object detection challenge in computer vision aims at finding and identifying items in an picture or video. Single-stage and two-stage object detection algorithms are the two basic types of object detection techniques. The one-stage object detection methods, carry out object categorization, and bounding-box regression without the use of pre-generated region proposals. In the present study, we trained YOLOv8 and YOLOv5 one-stage object detection algorithms. 80 trainings epochs in al has been chosen, with a training batch size of 16, and the beginning learning rate is 0.01. The detection performance of models of different sizes was studied after training the most sophisticated one-step object identification algorithms, YOLOv5 and YOLOv8. Table 1, displays the test set's YOLOv8 and-YOLOv5 detection results.

Table 1. Results comparison of different methods

Method	Precision	Recall	mAP@0.5	mAP@0.95
YOLOv5s	0.803	0.864	0.86	0.566
YOLOv5n	0.818	0.785	0.805	0.504
YOLOv8s	0.856	0.88	0.905	0.575
YOLOv8n	0.813	0.861	0.871	0.603

YOLOv8s demonstrated an advantage over the other models in terms of accuracy and efficiency. Indeed, it presents a map of 90,5% compared with YOLOv8n with 87% and both outperform YOLOv5s and YOLOv5n which presents a map of 86%, same for precision metrics and recall, the YOLOV8s showed superiority than the other YOLOv5 algorithms. Figure 8 displays the final visualizations of the YOLOv8s detection model, and Figure 9 displays those of YOLOv5 detection model, for the same testing of several types of solar cell defect photos.

Table 2 and Figure 6 demonstrate the YOLOv8s detection results for various classes. The YOLO series' mean mAP (IoU=0.5:0.95) is higher than that of the other algorithms, indicating that its prediction boxes are more accurate at locating and matching objects at greater IoU thresholds. The mAP score of the faults printing error, short-circuit, star crack, and horizontal dislocation is more than 99.4, for the faults finger, think line varies from 76 to 85, which reveals that YOLOv8 applied can classify with precision the various types of faults studied.

Table 2. Results of YOLOv8s detection for several classes on this dataset

Method	Precision	Recall	mAP@0.5	mAP@0.95
Black-core	0.778	0.889	0.915	0.906
Crack	0.476	0.769	0.64	0.441
Finger	0.763	0.758	0.766	0.423
Horizontal-dislocation	0.984	0.978	0.994	0.564
Printing-error	0.921	1	0.995	0.619
Short-circuit	1	1	0.995	0.989
Star-crack	1	0.859	0.995	0.38
Thick-line	0.823	0.757	0.848	0.479
Vertical-dislocation	0.956	0.907	0.984	0.38

As observed in Figure 9, YOLOv5s exhibits an incomplete detection with a modest degree of confidence when complicated background noise is present. While the non-uniform, complicated background in Figure 10 does not interfere with the new YOLOv8s model, in this study all image defects are detected. For example, the start crack has been detected by YOLOv8 but for YOLOv5 there is no fault in the cell, the same for the printing error defect there is some fault not detected by YOLOv5. The comparison demonstrates that the new version of the YOLOv8s model has outstanding generalization performance, more precise detection outcomes, and may record the essential faults details.
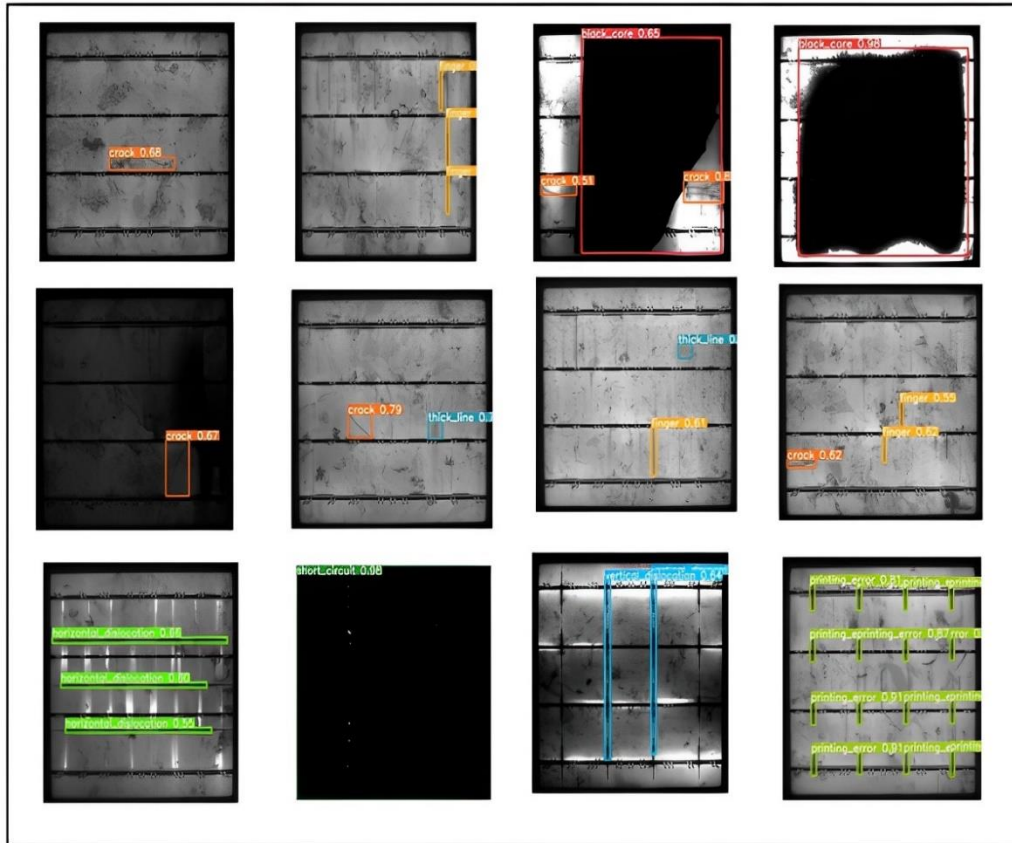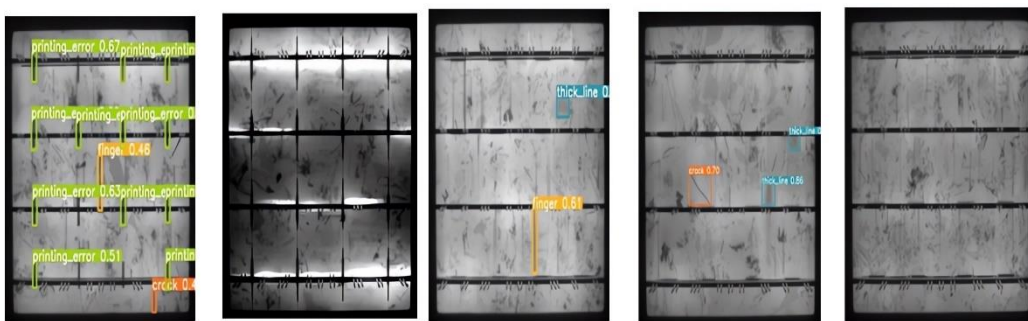
Figure 8. The result of YOLOv8s defects detection

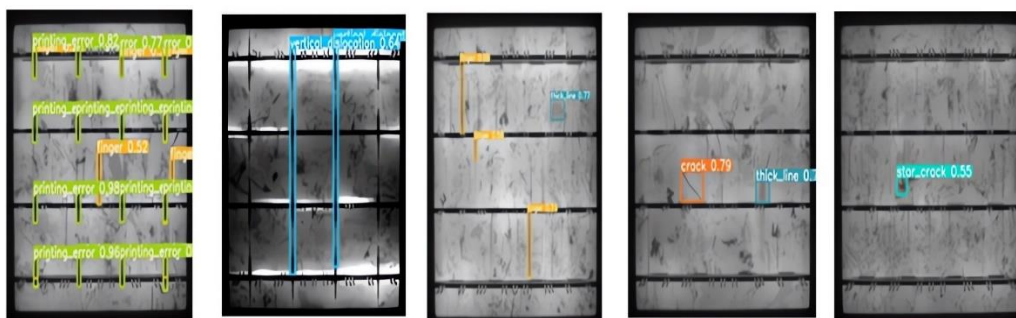Figure 9. YOLOv5s detection fault result

Figure 10. YOLOv8s detection fault result

The confusion matrix for classifying PV faults is shown in Figure 11, which performs really well, that the model is extremely well-trained, and that it does so properly with the unobserved dataset. Evidently, there is a minor ambiguity between the start crack and background, and also between the black core and background, for all defects that are taken into consideration. The performance of the model as a whole is unaffected by this.
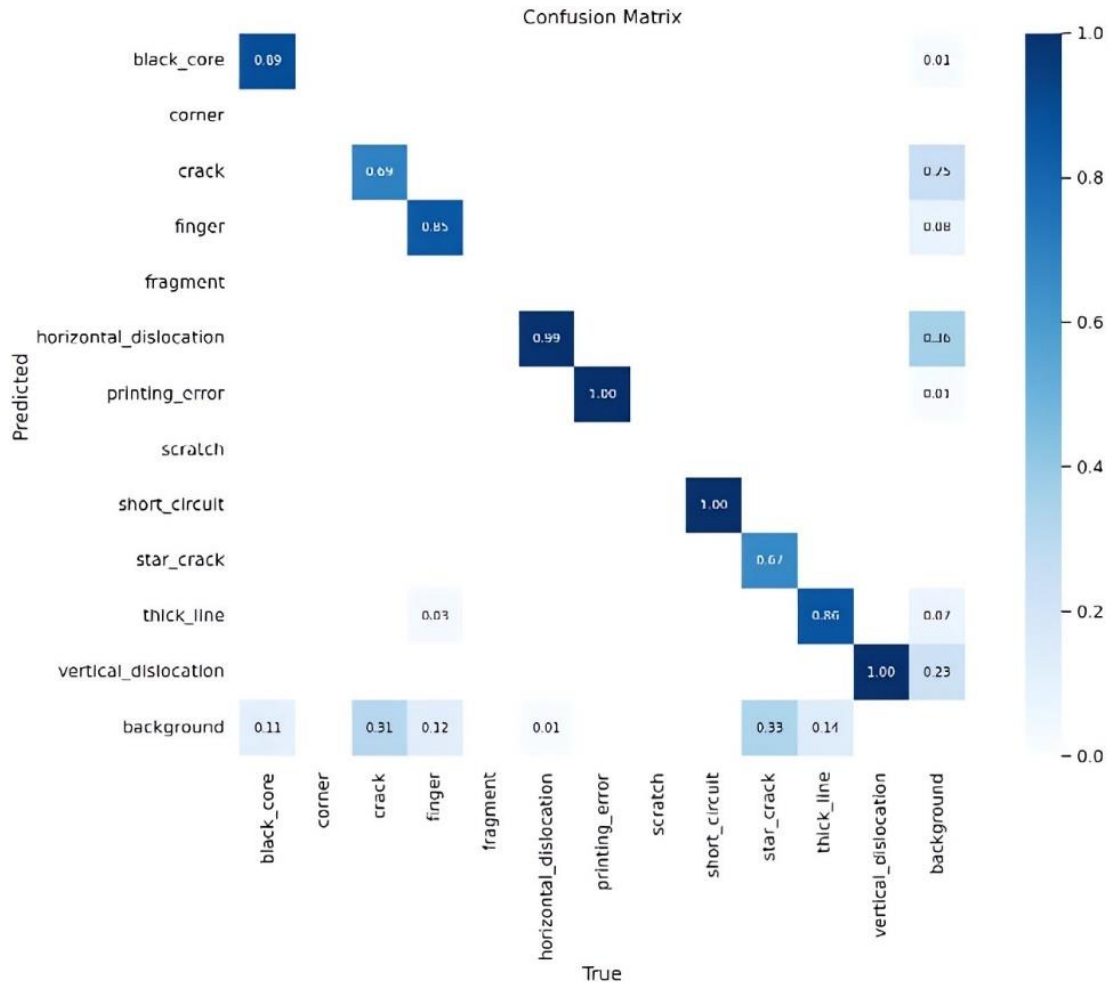

Figure 11. The confusion matrix achieved by YOLOv8s

Figure 12 makes it evident that the precision-recall curve is approaching the space's upper right corner (1.1), demonstrating the high precision of the model at high recall levels. This indicates that the model is performing well at detecting positive samples while reducing the impact of false positives. The YOLOv8s models improve our dataset somewhat over YOLOv5. When compared to the other models, YOLOv8s showed superiority in terms of accuracy and effectiveness. This outcome was anticipated because YOLOv8 is the most advanced object detection algorithm currently available, offering the best accuracy while also requiring a manageable amount of training time. These attributes make it a powerful tool for enhancing the quality control and inspection processes in industries where object detection is critical.

Figure 13 demonstrates that the YOLOv8s curve is higher than the YOLOv8n, YOLOv5s, and YOLOv5n curves. This signifies that the YOLOv8s detection accuracy is higher than the YOLOv5s detection accuracy, hence showing that the model exhibits greater stability. Overall, the YOLOv8s detection model described in this article has excellent accuracy and has improved the network's detection efficiency- in order to enhance applications for detecting faults in solar cells. Despite being less accurate than YOLOv8s, YOLOv5s performed well, placing third with strong general detection rates and training. Therefore, it is evident that YOLOv8 is the preferable algorithm.
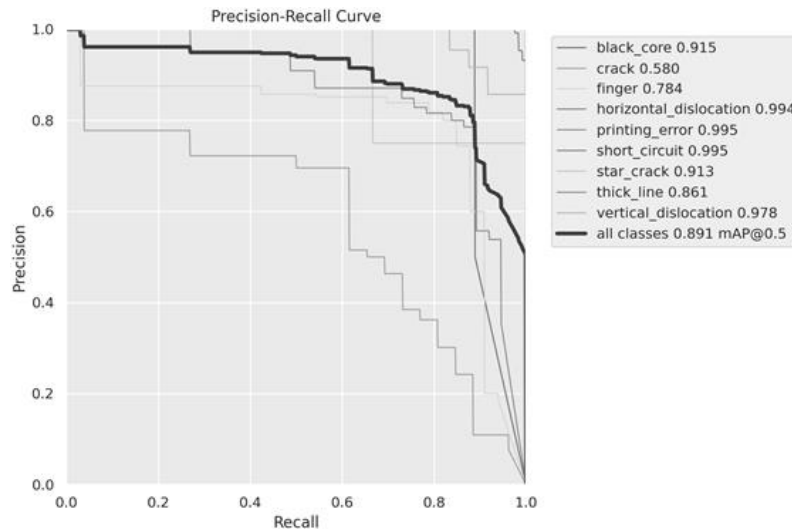
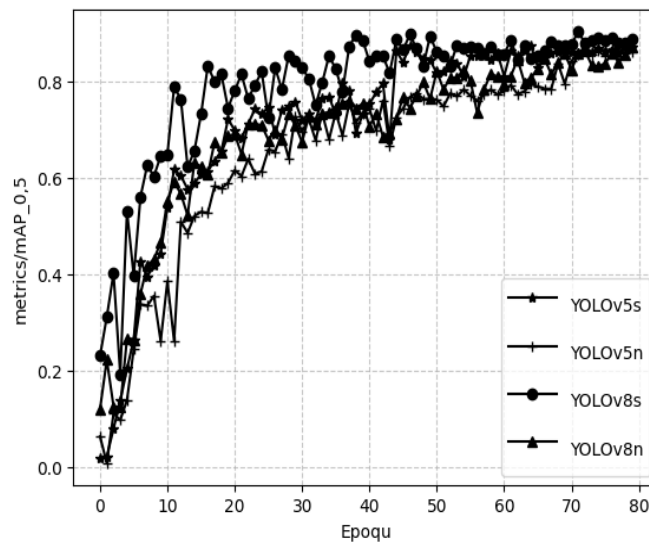Figure 12. Test results of the YOLOv8s model, precision–recall curve

Figure 13. Metric/mAP 0.5 results

4. CONCLUSION

This study employs computer vision techniques to detect various errors in solar cell manufacture using the YOLOv8 architecture; this new technique can address the drawbacks of conventional detection techniques, including their rigidity, slowness, and reduced accuracy. The experimental findings prove that the proposed approach can effectively and accurately detect numerous defaults that are present on solar cell surfaces, short-circuit, fracture, and horizontal dissolution. According to the test results, the faulty solar cell has been preciserly determined, in fact, the two object detection algorithms applied, namely YOLOv5 and YOLOv8, have shown high precision in the detection of twelve solar cell faults. The mean average precision in YOLOv8s is 90.5%, and the recall rate is 85.2%. The YOLOv8s model exhibited superior performance in terms of both accuracy and efficiency compared to the other models. YOLOv8 has proven to be the most advanced object detection system. The best accuracy is achieved while requiring a reasonable training time. Indeed, the optimal balancing of speed and accuracy can be accomplished using YOLOv8; this algorithm is best suited for field use in large-scale solar photovoltaic cell production. Due to the effectiveness of YOLOv8's detection, this framework is very helpful in the practice of smart factories to perform intelligent tests to detect flaws in these solar cells, which is crucial to ensuring reliability, which is essential for the stability and safety of the system.

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