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Real-Time Solar Cell Defect Detection Using Optimized YOLOv5 with Attention and Multi-Scale Augmentation

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Abstract: This paper presents an optimized YOLOv5-based model for accurate detection of solar cell surface defects. The model incorporates advanced data augmentation techniques and a Channel Attention (CA) mechanism to enhance feature extraction and robustness. Additionally, a decoupled detection head is introduced to improve classification and localization performance. Experimental results demonstrate significant improvement in detection accuracy and real-time performance compared to the standard YOLOv5 model.

Index terms - *— Solar Cell Defect Detection, YOLOv5, Deep Learning, Data Augmentation, Channel Attention, Decoupled Head, Object Detection, Computer Vision*

1. INTRODUCTION

With the growing demand for clean and renewable energy, solar energy has emerged as one of the most reliable and widely used sources. Solar cells play a crucial role in converting sunlight into electrical energy; however, defects such as cracks, black cores, and short circuits during manufacturing can significantly reduce their efficiency and lifespan. Therefore, accurate and timely detection of surface defects is essential to ensure high-quality solar cell production and improved energy output.

Traditional defect detection methods mainly rely on manual inspection and conventional machine vision techniques. These approaches are time-consuming, labor-intensive, and highly dependent on human expertise, often leading to errors such as missed detections and misclassification. Although deep learning techniques, especially Convolutional Neural Networks (CNNs), have shown strong performance in image recognition tasks, their direct application to solar cell defect detection faces several challenges, including limited datasets, diverse defect patterns, background interference, and difficulty in detecting small defects.

Recent advancements in object detection models, particularly the YOLO (You Only Look Once) series, have demonstrated excellent performance in terms of speed and accuracy. Among them, YOLOv5 provides an optimal balance between computational efficiency and detection precision, making it suitable for real-time applications. However, the standard YOLOv5 model still requires improvements to effectively handle the complexity of solar cell defect detection. To address these limitations, this paper proposes an optimized YOLOv5 model that integrates advanced data augmentation techniques, a Channel Attention mechanism for enhanced feature extraction, and a decoupled detection head to improve classification and localization performance. This approach aims to achieve higher accuracy, robustness, and real-time defect detection capability.

2. LITERATURE SURVEY

a) Exploiting convolutional neural networks with deeply local description for remote sensing image classification:

The high energy density of layered Li-rich Mn-based oxide cathode materials (LRMO) has garnered a lot of interest. However, the actual use is hindered by the low cycle stability, rate capability, and fast voltage depreciation. This article describes a unique approach to designing LRMO modified by silica-coated silver nanowires (AgNWs@SiO2). AgNWs@SiO2 can improve oxygen vacancy, speed up Li+ transport kinetics, and aid in heat dissipation in LRMO. Consequently, compared to the untreated LRMO (65.2% after 500 cycles at 25 °C and 37.8% after 110 cycles at 60 °C), the AgNWs@SiO2 modified LRMO provides a greater capacity retention of 71.6% (after 500 cycles at 25 °C) and 58.5% (after 200 cycles at 60 °C) at 1C. In the meanwhile, the AgNWs@SiO2 modified LRMO has a capacity retention of 50.6% after 1000 cycles at 3C and a high-rate discharge specific capacity of 105.4 mAh g-1 at 10C (the untreated LRMO only retains 19.3% after 600 cycles at 3C). Additionally, in the cell built with a Si@C anode, the AgNWs@SiO2 modified LRMO also shows good electrochemical performance. This work offers a viable approach for the potential real-world implementation of next-generation high energy density lithium-ion batteries.

b) Convolutional recurrent deep learning model for sentence classification:

The demand to handle unstructured text data intelligently and derive various kinds of information from it is growing along with the amount of unstructured text data that people generate in general and on the Internet. Recurrent neural networks (RNNs) and convolutional neural networks (CNNs) have been used in natural language processing systems with comparable, impressive outcomes. An excellent method for extracting higher level properties that are not affected by local translation is the CNN. However, because the convolutional and pooling layers are local, it necessitates stacking several convolutional layers to capture long-term relationships. To address this issue, we present a hybrid CNN and RNN system in this research. In short, we train initial word embeddings using an unsupervised neural language model, which are then further refined by our deep learning network. The model is then initialized using the network's pre-trained parameters. Finally, a collection of feature maps learnt by a convolutional layer with long-term dependencies learned via long-short-term memory are combined with previously acquired information in the suggested framework. Empirically, we demonstrate that our method produces exceptional performance on several sentiment analysis benchmarks with only minor hyperparameter modification and static vectors. Our method outperforms a number of current methods in terms of accuracy, and our results are competitive with the state-of-the-art on the Stanford Sentiment Treebank data set (48.8% fine-grained accuracy and 89.2% binary accuracy, respectively) and the Stanford

Large Movie Review data set (93.3% accuracy). Our method plays a major part in lowering the number of parameters and building the convolutional layer first, then the recurrent layer to replace the pooling layer. Our findings demonstrate that using an effective framework with fewer parameters and great performance, we were able to capture long-term dependencies and lessen the loss of specific, local information.

c) A novel text structure feature extractor for Chinese scene text detection and recognition

Training deeper neural networks is more challenging. In order to facilitate the training of networks that are far deeper than those previously employed, we provide a residual learning approach. Rather than learning unreferenced functions, we explicitly reformulate the layers as learning residual functions with reference to the layer inputs. We present thorough empirical data demonstrating that these residual networks may improve accuracy with far greater depth and are simpler to tune. We assess residual nets up to 152 layers deep on the ImageNet dataset, which is 8× deeper than VGG nets [40] but still less complicated. On the ImageNet test set, an ensemble of these residual nets achieves an error of 3.57%. In the ILSVRC 2015 classification task, this outcome took first place. Additionally, we analyze CIFAR-10 with 100 and 1000 layers. For many visual identification tasks, the depth of representations is crucial. We achieve a 28% relative improvement on the COCO object identification dataset only because of our incredibly deep representations. Our contributions to the ILSVRC & COCO 2015 competitions1, where we also took first place in ImageNet detection, ImageNet localization, COCO detection, and COCO segmentation tasks, are based on deep residual nets.

d) Zhang, Z., Wang, L., Wang, J., Jiang, X., Li, X., Hu, Z., Ji, Y., Wu, X. & Chen, C. Mesoporous silica-coated gold nanorods as a light-mediated multifunctional theranostic platform for cancer treatment. Adv. Mater. 24, 1418-1423:

Mesoporous silica-coated gold nanorods (Au@ SiO2) are developed by X. Wu, C. Chen, and colleagues as a flexible platform for heat, chemotherapy, and imaging. Thus, Au@ SiO2 retains the special properties of gold nanorods and mesoporous silica nanoparticles while simultaneously offering a new feature: light-controlled drug release. Such multifunctional theranostic devices with integrated functionalities are essential for maximizing therapeutic effectiveness and enhancing treatment regimen safety. They will open the door to customized treatment by offering additional chances for on-demand therapy.

e) SSD: Single Shot MultiBox Detector:

We provide a technique that uses a single deep neural network to identify items in photos. Our method, called SSD, discretizes the bounding box output space into a series of default boxes across various aspect ratios and sizes for each feature map position. The network creates scores for each item category's existence in each default box during prediction time and modifies the box to better fit the object form. In order to naturally manage objects of varied sizes, the network also incorporates predictions from numerous feature maps with different resolutions. Because our SSD model incorporates all computing in a single network and avoids proposal creation and the following pixel or feature resampling stage, it is simpler than approaches that need object proposals. Because of this, SSD is simple to implement into systems that need a detection component and to train. Experimental findings on the PASCAL VOC, MS COCO, and ILSVRC datasets verify that SSD is significantly quicker and offers a unified framework for both training and inference, with accuracy equivalent to approaches that include an additional object proposal phase. Even with a smaller input picture size, SSD provides significantly higher accuracy than other single stage techniques. SSD outperforms a similar state-of-the-art Faster R-CNN model, achieving 75.1% mAP for input and 72.1% mAP on the VOC2007 test at 58 FPS on an Nvidia Titan X.

3. METHODOLOGY

i) Proposed Work:

The proposed work focuses on developing an optimized YOLOv5-based model to accurately detect and classify solar cell surface defects in real-time. To overcome the limitation of small and insufficient datasets, multiple data augmentation techniques such as Mosaic, Mixup, HSV transformation, scaling, and flipping are applied to enhance dataset diversity and improve model robustness. These techniques help the model generalize better and detect defects under varying conditions.

Furthermore, a Channel Attention (CA) mechanism is integrated into the YOLOv5 architecture to improve feature extraction by focusing on important channel information and suppressing irrelevant features. In addition, the traditional detection head is replaced with a decoupled head to separate classification and localization tasks, reducing conflict between them and improving detection accuracy. The overall system ensures high precision, better defect localization, and real-time performance, making it suitable for practical solar cell inspection applications.

ii) System Architecture:

The system architecture for solar cell surface defect detection follows a structured pipeline starting from dataset input to final performance evaluation. Initially, solar cell images are collected as input data, which contain various types of defects. These images are then passed through a data preprocessing stage where multiple augmentation techniques such as Mosaic, Mixup, HSV transformation, flipping, and scaling are applied. This step enhances dataset diversity and improves the model's ability to detect defects under different conditions, especially when training data is limited.

After preprocessing, the dataset is divided into training and testing sets. The training data is used to build and train the detection models, including Faster R-CNN, YOLOv5, and the optimized YOLO-based model. Among these, the optimized YOLOv5 model is the primary focus due to its real-time performance and improved accuracy. During testing, the model's performance is evaluated using key metrics such as accuracy, precision, recall, and F1-score. The final output of the system is the detection and localization of defects in solar cells, enabling efficient quality inspection in real-time applications.

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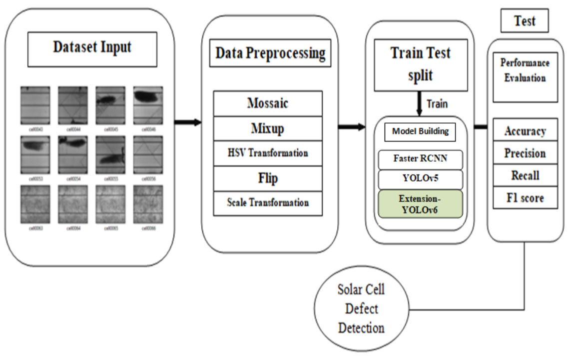

Fig1 proposed architecture

iii) Modules:

1. Dataset Collection Module

This module collects solar cell images from datasets such as ELPV and PVEL-AD. It ensures the availability of labeled images containing different types of defects for training and testing.

2. Data Preprocessing & Augmentation Module

This module enhances the dataset using techniques like Mosaic, Mixup, HSV transformation, flipping, and scaling. It improves data diversity, reduces overfitting, and helps in better feature learning.

3. Data Splitting Module

The dataset is divided into training and testing sets. This helps in evaluating the model performance effectively and avoids overfitting during training.

4. Model Building Module

This module constructs the optimized YOLOv5 architecture by integrating Channel Attention (CA) and a decoupled head. It improves feature extraction and detection accuracy.

5. Model Training Module

The model is trained using the augmented dataset to learn defect features. It optimizes weights through multiple iterations to achieve high detection accuracy.

6. Defect Detection Module

This module detects and localizes defects in solar cell images using the trained YOLOv5 model. It identifies multiple defect types in real-time.

7. Performance Evaluation Module

This module evaluates the model using metrics such as Accuracy, Precision, Recall, and F1-score. It ensures the reliability and effectiveness of the system.

iv) ALGORITHMS:

1. YOLOv5 Algorithm

YOLOv5 is a one-stage object detection algorithm that performs object localization and classification simultaneously in a single forward pass. It divides the input image into grids and predicts bounding boxes, object confidence scores, and class probabilities. Due to its high speed and accuracy, YOLOv5 is well-suited for real-time solar cell defect detection tasks.

2.YOLOv6 Algorithm

YOLOv6 is an advanced one-stage object detection algorithm designed for high-speed and efficient real-time applications. It performs object localization and classification simultaneously in a single forward pass through the network. YOLOv6 introduces an optimized backbone, neck, and efficient decoupled head architecture to improve detection accuracy and inference speed. It divides the input image into grids and predicts bounding boxes, object confidence scores, and class probabilities with enhanced precision. Due to its lightweight design and superior performance, YOLOv6 is highly suitable for real-time solar cell defect detection tasks.

4. EXPERIMENTAL RESULTS

The proposed optimized YOLOv5 model was evaluated using publicly available datasets such as ELPV and PVEL-AD to assess its performance in detecting solar cell surface defects. The model was trained on augmented data using techniques like Mosaic, Mixup, HSV transformation, scaling, and flipping, which significantly improved the diversity of the dataset and enhanced the model's robustness. The integration of the Channel Attention (CA) mechanism and decoupled detection head further improved feature extraction and detection accuracy, especially for small and complex defects.

The experimental results demonstrate that the proposed model achieves a high mean Average Precision (mAP) of 96.1% on the ELPV dataset and 87.4% on the PVEL-AD dataset, showing a significant improvement of approximately 10.38% over the standard YOLOv5 model. Additionally, the model performs well in terms of accuracy, precision, recall, and F1-score, ensuring reliable defect detection and localization. The system also maintains real-time performance, making it suitable for practical industrial applications in solar cell inspection.

Accuracy: A test's accuracy is determined by its capacity to distinguish between healthy and ill cases. To gauge the accuracy of the test, find the percentage of examined instances that had true positives and true negatives. According to the computations:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: Precision is the number of affirmative cases or the classification's accuracy rate. The following formula is applied to assess accuracy:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: A model's ability to recognise every instance of a pertinent machine learning class is measured by its recall. The ratio of accurately predicted positive observations to the total number of positives indicates how well a model can identify class instances.

$$Recall = \frac{TP}{(FN + TP)}$$

mAP: Mean Average Precision is one ranking quality metric (MAP). It considers the number of relevant recommendations and their position on the list. MAP at K is calculated as the arithmetic mean of the Average Precision (AP) at K for each user or query.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{ the AP of class } k$$

$$n = \text{ the number of classes}$$

F1-Score: An accurate machine learning model is indicated by a high F1 score. combining precision and recall to increase model correctness. The accuracy statistic quantifies the frequency with which a model correctly predicts a dataset.

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

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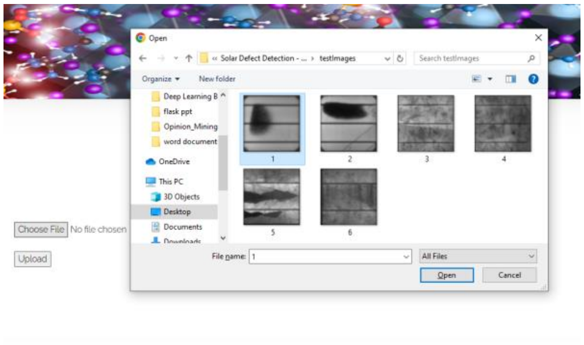

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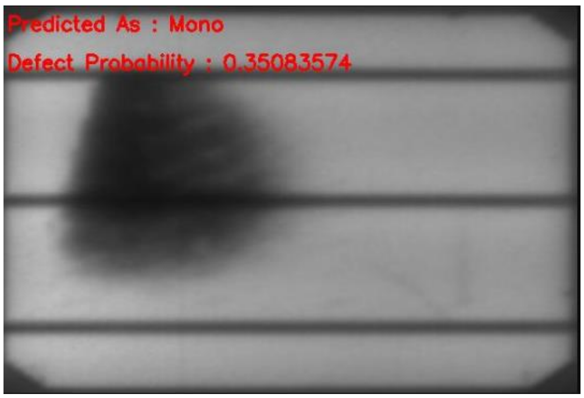

Fig3 results

5. CONCLUSION

This paper presents an optimized YOLOv5-based model for efficient and accurate detection of solar cell surface defects. By incorporating advanced data augmentation techniques, a Channel Attention (CA) mechanism, and a decoupled detection head, the proposed system effectively overcomes challenges such as limited datasets, diverse defect types, and small feature detection. The model demonstrates significant improvement in detection accuracy and robustness compared to the standard YOLOv5 approach.

Experimental results confirm that the proposed method achieves high performance in terms of mAP, precision, recall, and F1-score while maintaining real-time detection capability. Therefore, the system can be effectively applied in industrial environments for automated solar cell inspection, improving product quality and production efficiency.

6. FUTURE SCOPE

The proposed system can be further enhanced by incorporating more advanced deep learning architectures such as YOLOv7 or transformer-based models to improve detection accuracy and efficiency. Future work can also focus on expanding the dataset with more diverse and real-world defect samples to improve generalization and robustness.

Additionally, integrating the system with edge devices and IoT-based smart manufacturing systems can enable real-time on-site defect detection in industrial environments. Further improvements may include handling extremely small or complex defects, reducing computational cost, and developing a fully automated quality inspection system for large-scale solar panel production.

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