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YOLOv5 Optimization for the Identification of Surface Defects in Solar Cells

[1]P Praveen Yadav, [2]B Santhosh Kumar, [3]M Raghavendra Reddy

[1] [3]Assistant Professor, Computer science and Engineering Department, G.Pulla Reddy Engineering College(Autonomous):Kurnool.
[2]Associate Professor, Computer science and Engineering Department, G.Pulla Reddy Engineering College(Autonomous):Kurnool.

Abstract— In light of the dynamic solar cell picture background information, varied problem morphology, and large-scale differences, a solar cell defect identification approach utilizing an enhanced YOLO v5 algorithm is suggested. A tiny predicted defect head is added to the model's network structure, which improves target detection accuracy at various scales. Lastly, the model's feature extraction capability is further enhanced through the addition of the ECA-Net attention mechanism. Initially, the CSP module incorporates the deformable convolution to attain an adaptable learning scale as well as perceptual field size. The K-means++ clustering anchoring box algorithm, the CIOU loss function, and the Mosaic & Mix-up fusion data improvement are used in this research to better optimize & enhance the YOLO v5 algorithm. As demonstrated by the experimental results, the new YOLO v5 method accomplishes 89.64% map for a model trained on a solar cell EL image the data set, a percentage 7.85% higher than the original algorithm's map. It also reaches a speed of 36.24 frames per second, which allows it to meet real-time requirements while still completing the solar cell defect identification task with greater accuracy.

INTRODUCTION

Currently, people's focus is on developing and using new energy sources due to the combined pressures of environmental pollution with the growing traditional energy crises. Solar energy has gained popularity as a new energy source that develops quickly because of its numerous uses, low cost, security, and dependability. Solar panels are crucial parts of the photovoltaic power generation system. However, because silicon crystal plates are easily damaged during production or installation, defects can seriously jeopardize not only the safety of people and property but also the effectiveness of solar energy power generation. Consequently, it is crucial to research techniques for detecting solar cell defects. Using a semiconductor charge-coupled detector (CCD) or an In GaAs camera, electroluminescence (EL) imaging entails stimulating the PV module with a forward bias current and then utilizing the excited state's infrared light produced by the solar cell for imaging. Electroluminescence imaging has the benefit of being non-destructive and non-contact. It can be used to detect process defects such as finger interruption and tiny cracks that are invisible to conventional imaging systems. Additionally, it can prevent imaging blur from lateral thermal propagation. Due to its superior performance, luminescence imaging has taken over as the primary method for detecting defects in solar cells. A high work load, low efficiency, undue reliance on the personal knowledge of O&M engineers, and an unguaranteed lack of inspection accuracy characterize traditional visual inspection, which needs operation and maintenance experts to carry instruments and examine solar cells one by one. Researchers have suggested using traditional computer vision, which is based upon manually extracting features and classifiers, to precisely and automatically identify image abnormalities. By lowering the probability components of line or strip flaws to zero, Tsai et al.'s approach of identifying defects in polycrystalline solar cells eliminates potential defects from EL pictures. An efficient technique for detecting infrared (IR) and photoluminescence (PL) images of small-grain wafers of silicon is the classification recognition approach Dement et al. presented, based on support vector machines and local descriptors. But manual descriptor extraction is the foundation of classical computer vision, which is weak in terms of robustness and generalization and necessitates a great deal of parameter alteration .

Target identification, picture classification, or semantic segmentation have all benefited greatly from the widespread adoption of deep learning models represented by convolution neural networks in recent years. The direct application of sophisticated deep learning models for identifying surface defects in the solar cell EL images presents inapplicable issues, primarily because sunlight cell detection of defects is susceptible to disruption from complex backgrounds. Convolutional neural networks, on the other hand, have been developed for natural scene images. Cracks and finger interruptions are examples of micro defect features that tend to diminish as network training and down sampling go. Solar cells exhibit variability in the shape or the same class of faults. Solar cell fault detection is difficult because of the aforementioned issues. These are the challenges that deep learning-based photovoltaic cell fault identification faces. Consequently, early in the research process, two-order detection models like the R-CNN collection and R-FCN, etc., that are predicated on the concept of candidate areas are frequently employed. These algorithms recognize things with a high degree of precision, but they do so slowly. The precision and swiftness of target detection are continuously being improved by the first-order detection model, represented by the YOLO series algorithms, thanks to the constant efforts put forth by scientific researchers, and the detection effect is growing daily. An anchor box is used by the YOLO family of algorithms, a common first-order target detection technique, to integrate target localization and categorization. YOLO v1, YOLO v2, as well as YOLO v3 are the three versions of the YOLO household of algorithms that have been released thus far. The YOLO research team proposed all of these versions, and YOLO v3 is regarded as a significant improvement in the speed and performance for the YOLO household of algorithms. Meanwhile, YOLO v4 as well as YOLO v5 have been released by separate research teams. Target detection professionals have praised the fact that the YOLO v5 recognition model is fully built in Python (Pytorch) and is both faster and smaller than the previous four generations of models. Notably, researchers from several research directions have enhanced the initial YOLO v5 modelling according to the features of their detecting targets, which has resulted in a better YOLO v5 algorithm that is exceptional in many study fields. Li et al. proposed an enhanced YOLO v5 go after detector for infrared images, which reduced the network parameters while maintaining detection accuracy. They achieved this by incorporating an improved attention module into the residual module and incorporating the cross-stage-partial-connections (CSP) section to their improved model. By combining cantered and scale calibration, enhancing the loss of cross-entropy function, and including the Sandglass module in the residual module, Luo et al. presented an enhanced YOLO v5-based aviation target identification technique that resulted in a significant increase in detection speed and precision. By swapping out the original prediction head for the Transformer prediction head, boosting the number of forecasting heads, and adding an attention mechanism, Zhu et al. created the TPH-YOLO v5 model, which saw a significant increase in detection accuracy and speed—roughly 7%—over the original performance. In order to address the dataset's class imbalance during training and significantly enhance the YOLO v5 detecting model's classification performance, Kim et al. suggested an online by copying and past and hybrid data improvement technique. By incorporating a network called the Siamese for classifying binary data at the neck, Misedit et al. devised an inexpensive YOLOv5 surveillance model to detect loop closures and visited networks . Following the examination and illustration above, it can be concluded that this first-order detector YOLO v5, which has a strong real-time processing capabilities and minimal hardware requirements, is crucial for target identification and may be transferred to mobile devices enabling real-time monitoring. Based on this, the research suggests an enhanced YOLO v5 simulation to simulate the three distinct surface defects of solar cells: finger interruption, black core, and cracks. The enhanced YOLO v5 network design incorporates deformable convolution into the CSP module to facilitate efficient extraction of imperfections of varying sizes and shapes. Additionally, the ECA-Net consideration module is incorporated into the Neck section to enhance detection performance via cross-channel interaction. Simultaneously, the model structure is refined and a prediction the head is added to accomplish four-scale include defect detection and enhance the precision of defect detection. Lastly, using experiments like ablation tests and an examination of conventional techniques, the improved model's detection impact is objectively assessed in this paper. The findings demonstrate that the new model significantly increases the precision of cell defect detection while maintaining real-time detection.

RELATED WORK

A critical analysis of renewable energy and sustainable development

In order to address the current state of the environment, sustainable development will need to take long-term, prospective measures. The most practical and efficient option in this context seems to be the use of renewable energy resources. Sustainable development and renewable energy are therefore closely related. This study presents an extensive discussion of projected future energy use patterns and the resulting environmental effects (with particular emphasis on precipitation of acids, stratospheric ozone depletion, and the greenhouse effect). In addition to renewable energy technologies, several remedies for the state of the environment are identified. A practical case study and an illustration are provided to demonstrate the relationships between energy from renewable sources and sustainable development. Many topics pertaining to sustainable development, renewable energy, and the environment are explored from both present and future angles throughout the article. Researchers and engineers working in the field of energy should find the conclusions and suggestions made in this study to be helpful.

Increasing the solar panel's efficiency: A thorough analysis

The use of solar panels to produce clean, green electricity is becoming more and more common in the realm of alternative energy sources. Conversely, as the outside temperature rises, the photovoltaic efficiency decreases. A temperature increase over STC results in a 0.33% decrease in energy production. Therefore, it's possible that the solar panel's generated electricity won't be enough to complete the task. Acknowledging the fact that space for an extra solar panel to make up for the reduced power generation may not be possible for certain applications, such freestanding electric vehicles, is vital. It is possible to lessen this extreme heat by putting the cooling measures into action. Active and passive procedures are two of the many cooling techniques that have been used. In order to maximize solar panel efficiency, this article reviews integrating thermoelectric generators (TEG) with solar panels and several cooling techniques.

Methods for identifying flaws and contaminants in crystalline silicon for solar cells

Grains restrictions, dislocations, and transitional metals are examples of flaws and contaminants that reduce the efficacy of multicrystalline solar cells. These flaws frequently differ in density from grain each grain. The total cell efficiency is decreased when "good grains" with high minority carriers diffusion length are shunted by "bad grains" with low minority messenger diffusion length, which also produce low open circuit voltage. It was discovered that regions of low diffusion length are not effectively improved by gettering, and that transition metal clusters are more likely to be found in "bad grains" than in "good grains." The discovery of these lifetime-limiting flaws is the main goal of materials research in solar energy. This article reviews the current understanding of lifetime-limiting defects in solar cells, discusses new and emerging techniques such as X-ray beam-induced current, X-ray fluorescence microprobe, and X-ray absorption spectromicroscopy, and summarizes the benefits and drawbacks of traditional analytical tools.

Control and Defect Detection in Solar Cells: The Function of Defects in Solar Cells

Impurities and imperfections in the substrates have a significant influence on how well commercial solar cells function. Sunlight cell quantum efficiency and carrier lifetime are reduced by defects that create deep levels of energy in the semiconductor bandgap. Techniques for electrical characterization that reveal details about the concentration, geographical distribution, and physical origin of defects are necessary for a thorough understanding of their characteristics. This work describes the experimentation methods that are available in our laboratory. On the other hand, an intermediate band that forms in a semiconductor's midgap can significantly increase the effectiveness of single junction solar cells. If deep level faults are present in sufficient concentration, they can form the intermediate band. This study also presents experimental findings that support the intermediate band development.

Defects' effects on solar cell properties

Most industrial silicon solar cells exhibit current-voltage (I-V) characteristics that somewhat differ from the exponential behavior predicted by textbook knowledge. Since the recombination current frequently exhibits an ideality factor bigger than 2 in a broad bias-range and may be orders magnitude larger than anticipated given the given material quality, it cannot be described by classical theory either. Occasionally, despite the margins of the cell being perfectly insolated, ohmic shunts are present. The features under reverse bias are either super-linear or linear even without the presence of such shunts, although saturation would be expected using conventional methods. Brokendown tends to happen at roughly -15 V reverse bias, or even lower, rather than the anticipated -50 V. This is especially true for multicrystalline cells. Cells with long-lasting abnormalities are usually the source of these aberrations. The origin of silicon solar cells' nonideal I-V characteristics is reviewed in this work along with some fresh findings on recombination involving linked defect levels .

Methods of production and inspection for solar cell modules

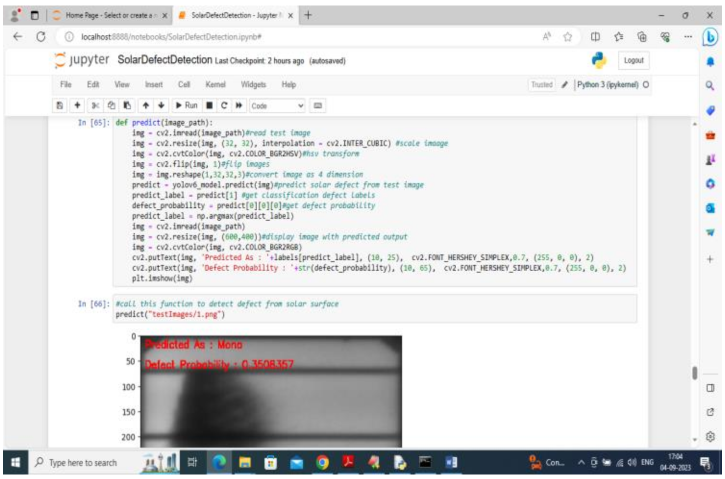
The rapid rise of photovoltaic (PV) generators in response to the need for renewable energy has resulted in a variety of size construction projects. Large-scale, varied terrain construction necessitates the use of quick and precise monitoring technology for reliable electricity production and upkeep. This study set out to create a technique that would allow solar module failure and normal functioning to be analyzed. To do this, thermal and optical infrared sensors were mounted on unmanned aerial vehicles (UAVs), resulting in orthography images of temperature data. The following are the findings from this study: The analysis for the temperature shifts features of the solar panel and cell revealed that the unusual module and cell displayed a larger shift in temperature than the normal module as well as cell, and the abnormal state panel and cell can be accurately identified by the unusual heat generation of the panel and cell through the geographical distribution of the temperature. This technique, which combines the use of optical and thermal infrared sensors that have various resolutions at the same time, is able to generate accurate spatial information. Finally, it is determined that the solar module inspection technique utilizing the acquired UAV-based thermal infrared sensor can be helpful for safety inspection and monitoring of the quickly growing solar power generation facility.

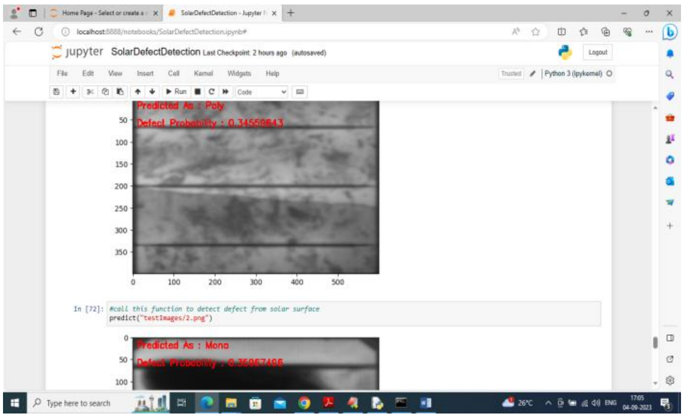
METHODOLOGY

1. Calculate metrics: This module requires us to compute metrics.
2. Training faster RCNN algorithm: This module was used to train the RCNN.
3. Training existing FRCNN: With the help of this module, we trained the GA-KELM genetic elm.
4. Training yolov5 algorithm : This module allowed us to train the Yolov5 algorithm.
5. Training yolov6 algorithm: This module allowed us to train the Yolov6 algorithm.
6. All algorithm performance graph: This module allowed us to obtain the performance graphs for every algorithm.

RESULT AND DISCUSSION

The screen above defines the prediction function for predicting defects using the Yolov6 extension model. The defect name, "MONO," and defect probability, "0.35%," are displayed in the image's red text.





Defect type and identified probability for other photos are displayed in the above screen.

CONCLUSION

In order to improve the extraction of features capability and achieve defect detection at various scales, a new YOLO v5 target identification model is proposed in this paper for identifying the features of solar cell defects. This model includes a prediction head, an ECA-Net attention mechanism, a deformable convolutional neural networks CSP module, and altered network structure. While this is going on, this paper employs multi-model integration techniques, K-means++ clustering anchor box methodology, and mosaic and MixUp scale fusing data improvement to optimize and improve the model. An average accuracy of 89.64%, a rise of 7.85% over the mAP of the previous detection approach, and a speed of 36.24 FPS are achieved by the enhanced target detection model, with notable enhancement effects, according to the comparison and ablation experiments. The following line of study aims to increase the detection model's lightness by reducing its complexity and achieving high detection speed through the processing of the detection model network pruning and distillation.

REFERENCES

[1] M. Köntges, I. Kunze, S. Kajari-Schröder, X. Breitenmoser and B. Bjørneklett, "The risk of power loss in crystalline silicon based photovoltaic modules due to micro-cracks", *Sol. Energy Mater. Sol. Cells*, vol. 95, no. 4, pp. 1131-1137, Apr. 2011.

[2] P. Rupnowski and B. Sopori, "Strength of silicon wafers: Fracture mechanics approach", *Int. J. Fract.*, vol. 155, no. 1, pp. 67-74, Mar. 2009.

[3] B. Du, R. Yang, F. Wang, S. Huang and Y. He, "Nondestructive inspection testing and evaluation for Si-based thin film and multi-junction solar cells: An overview", *Renew. Sustain. Energy Rev.*, vol. 78, pp. 1117-1151, Oct. 2017.

[4] T. Fuyuki and A. Kitiyanan, "Photographic diagnosis of crystalline silicon solar cells utilizing electroluminescence", *Appl. Phys. A Solids Surf.*, vol. 96, no. 1, pp. 189-196, Jul. 2009.

[5] M. Dhimish and V. Holmes, "Solar cells micro crack detection technique using state-of-the-art electroluminescence imaging", *J. Sci. Adv. Mater. Devices*, vol. 4, no. 4, pp. 499-508, Dec. 2019.

[6] M. Demant, T. Welschehold, M. Oswald, S. Bartsch, T. Brox, S. Schoenfelder, et al., "Microcracks in silicon wafers I: Inline detection and implications of crack morphology on wafer strength", *IEEE J. Photovolt.*, vol. 6, no. 1, pp. 126-135, Jan. 2016.

[7] B. Su, H. Chen, Y. Zhu, W. Liu and K. Liu, "Classification of manufacturing defects in multicrystalline solar cells with novel feature descriptor", *IEEE Trans. Instrum. Meas.*, vol. 68, no. 12, pp. 4675-4688, Dec. 2019.

[8] K. Firuzi, M. Vakilian, B. T. Phung and T. R. Blackburn, "Partial discharges pattern recognition of transformer defect model by LBP HOG features", *IEEE Trans. Power Del.*, vol. 34, no. 2, pp. 542-550, Apr. 2019.

[9] Q. Luo, Y. Sun, P. Li, O. Simpson, L. Tian and Y. He, "Generalized completed local binary patterns for time-efficient steel surface defect classification", *IEEE Trans. Instrum. Meas.*, vol. 68, no. 3, pp. 667-679, Mar. 2019.

[10] D.-M. Tsai, S.-C. Wu and W.-C. Li, "Defect detection of solar cells in electroluminescence images using Fourier image reconstruction", *Sol. Energy Mater. Sol. Cells.*, vol. 99, pp. 250-262, Apr. 2012.

[11] X. Qian, H. Zhang, C. Yang, Y. Wu, Z. He, Q.-E. Wu, et al., "Micro-cracks detection of multicrystalline solar cell surface based on self-learning features and low-rank matrix recovery", *Sensor Rev.*, vol. 38, no. 3, pp. 360-368, Jun. 2018.

[12] D.-M. Tsai, G.-N. Li, W.-C. Li and W.-Y. Chiu, "Defect detection in multi-crystal solar cells using clustering with uniformity measures", *Adv. Eng. Inform.*, vol. 29, no. 3, pp. 419-430, 2015.