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SOLAR CELL SURFACE DEFECT DETECTION BASED ON IMPROVED YOLO V5

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Abstract: This study introduces an advanced Solar Cell Surface Defect Detection method utilizing an improved YOLO v5, FaserRCNN and YOLOV6 algorithms. Addressing the challenges posed by complex image backgrounds, variable defect morphology, and large-scale differences, our approach incorporates deformable convolution in the CSP module for adaptive learning scale and perceptual field size. The integration of the ECA-Net attention mechanism enhances feature extraction capabilities, while the addition of a tiny defect prediction head improves detection accuracy across different scales. Optimization techniques, including Mosaic and MixUp data augmentation, K-meansCC clustering anchor box algorithm, and the CIOU loss function, contribute to superior model performance. Experimental results demonstrate an impressive accuracy of 97.14% for YOLOv5, outperforming Faster R-CNN's 90.66%. Further extension studies on YOLOv6, YOLOv7, and YOLOv8 reveal YOLOv6 as the most effective, achieving a remarkable accuracy of 98.28%. This research establishes a robust solution for solar cell defect detection, showcasing the efficacy of our proposed algorithm for industrial applications.

Index Terms *-Deep learning, YOLO v5, solar cell, defect detection, EL image, YoloV6 with VGG16*

INTRODUCTION

At the present stage, under the dual pressure of environmental pollution and the increasingly prominent traditional energy crisis, people have turned their attention to the development and utilization of new energy sources [1]. Due to the advantages of a wide range of applications, low cost, safety, and reliability, solar energy has become one of the mainstream new energy sources with high-speed development. Solar panels are important components of photovoltaic power generation, silicon crystal plates are fragile and fragile, and defects are easily produced by improper operation in production and installation [2], these defects cannot only affect the efficiency of solar cell power generation but also seriously threaten people's life and property safety [3].

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Vol 14,Issue 2,May 2024

Therefore, the study of solar cell defect detection methods is of great significance [4]. Electroluminescence (EL) imaging involves injecting a forward bias current into the PV module to put it in an excited state and then using a silicon charge-coupled device (CCD) or an InGaAs camera to capture the infrared light generated by the solar cell in the excited state for imaging. With the advantages of nondestructive and noncontact, electroluminescence imaging cannot only effectively detect tiny cracks, finger interruption, and other process defects that cannot be observed by conventional imaging systems, but also avoid blurring of imaging caused by lateral thermal propagation [5], [6]. Based on its excellent performance, electroluminescence imaging has become the main way of solar cell defect detection.

Develop an advanced Solar Cell Surface Defect Detection system by enhancing the YOLO v5 algorithm. Aimed at surpassing existing methods like Faster R-CNN, and extensions YOLOv6, YOLOv7, and YOLOv8, the objective is to optimize accuracy. YOLOv6, exhibiting superior performance, is selected for extension, ensuring precise and efficient detection of defects on solar cell surfaces.

Current solar cell defect detection methods lack efficiency in handling complex image backgrounds, variable defect morphologies, and large-scale differences. Existing algorithms like YOLO v5 and Faster R-CNN face challenges. This research addresses these issues, aiming to enhance accuracy and adaptability for robust solar cell surface defect detection.

Traditional visual inspection requires operation and maintenance engineers to carry instruments to inspect solar cells one by one, which is a high workload, low efficiency, and overly dependent on the subjective experience of O&M engineers, and the inspection accuracy cannot be guaranteed. To automatically and accurately identify defects in images, researchers have proposed traditionalcomputer vision based on manual feature extraction and classifiers [7]–[10]. Tsai et al. proposed a method for detecting defects in polysilicon solar cells based on the Fourier image reconstruction technique, which removes possible defects in EL images by setting the frequency components of line and strip defects to 0 [11]. Demant et al. proposed a classification recognition method based on local descriptors and support vector machines, which achieves effective detection of photoluminescence (PL) images and infrared (IR) images of small-grain silicon wafers [7]. However, traditional computer vision relies on manual extraction of descriptors, which requires a large number of parameter adjustments and has poor robustness and generalization capabilities.

1. LITERATURE SURVEY

[12] In this they utilize deep convolutional neural networks (CNN) for visual defect detection, employing both supervised and unsupervised learning approaches, with a focus on overcoming challenges in model training and achieving high detection accuracy. Potential drawbacks include complex model training, reliance on large labeled datasets, and challenges in adapting to diverse defect types, requiring continuous optimization for optimal performance. Algorithmic

ISSN 2229-6107 www.ijpast.in
Vol 14,Issuse 2,May 2024

challenges involve adapting to varied defect characteristics, application challenges in real-world scenarios, and data processing challenges related to handling diverse and unstructured datasets. Deep CNN-based defect detection presents a promising avenue for automated optical inspection, yet challenges persist in algorithmic adaptation, real-world applications, and data processing. Addressing these will further enhance industry and academic adoption.

[13] They introduce a cross-convolutional-layer pooling, our method leverages two consecutive convolutional layers for image representation, demonstrating superior performance in visual classification tasks and promising results in image retrieval. The method may face challenges in computational complexity, especially in the second scheme relying on densely sampled image regions. Additionally, fine-tuning for specific tasks might be required, impacting its general applicability. The approach may struggle with computational demands, particularly in the second scheme. Fine-tuning for diverse tasks could be necessary, potentially limiting the method's efficiency and ease of implementation in certain contexts. Our cross-convolutional-layer pooling method offers a novel approach to image representation, excelling in discriminating visual patterns. Despite computational challenges, it outperforms existing methods in various tasks, showcasing its potential in image recognition.

[14]This study introduces a methodology for remote sensing image classification using deeply local descriptors obtained from different scales of a CNN. Hellinger kernel, PCA, and two aggregation strategies enhance classification performance. Potential drawbacks include increased computational complexity due to the extraction of convolutional features from multiple scales and the application of Hellinger kernel and PCA, leading to higher processing requirements. Challenges may arise in handling diverse remote sensing scenarios, and the proposed methodology may face limitations in cases with insufficient training data or variations in image quality and characteristics. The presented approach leveraging deeply local descriptors, Hellinger kernel, PCA, and novel aggregation strategies demonstrates enhanced remote sensing image classification performance. Addressing computational demands and handling diverse scenarios remains a focus for future improvements.

[15]The paper introduces a hybrid CNN and RNN framework for sentence classification. Initial word embeddings are trained using an unsupervised neural language model, fine-tuned with deep learning, and combined with feature maps from a convolutional layer and long-term dependencies from LSTM. Despite achieving outstanding results, the framework may require careful hyperparameter tuning. The combination of CNN and RNN introduces complexity, potentially leading to increased computational demands and longer training times. The proposed system's reliance on pre-trained parameters and the need for hyperparameter tuning may limit its adaptability to different datasets. Handling domain-specific nuances and optimizing for diverse tasks could pose challenges. The hybrid CNN-RNN framework effectively balances capturing local

ISSN 2229-6107 www.ijpast.in
Vol 14,Issuse 2,May 2024

information and long-term dependencies. Despite challenges in parameter tuning, it outperforms existing approaches in sentiment analysis, showcasing efficiency and competitive accuracy across multiple benchmarks.

[16]Introducing a novel text structure feature extractor combining a Text Structure Component Detector layer and a residual network, optimizing feature extraction for both Chinese text detection and recognition, enhancing end-to-end system consistency. Potential drawbacks may include increased computational complexity due to the integration of specialized layers, requiring careful optimization. Additionally, the effectiveness across diverse datasets and languages may need further validation. Challenges may arise in adapting the proposed system to handle variations in text fonts and styles. Ensuring robustness across different scene conditions and text complexities remains a potential limitation for real-world applications. The presented text structure feature extractor demonstrates improved performance in both text detection and recognition, offering a unified solution for Chinese scene text extraction. Challenges in scalability and generalizability should be addressed for broader applicability.

2. METHODOLOGY

i) Proposed Work:

This study introduces an advanced framework for solar cell surface defect detection by leveraging an improved version of YOLOv5. Building upon the success of YOLOv5, which outperformed traditional methods like Faster R-CNN, the proposed system underwent an extension phase evaluating YOLOv6, v7, and v8. Among these, YOLOv6 exhibited superior performance over YOLOv7 and YOLOv8, leading to its selection as the extension model, primarily due to its remarkable accuracy. The system seamlessly integrates state-of-the-art deep learning techniques, enhancing both precision and efficiency in the detection of defects on solar cell surfaces. This research significantly contributes to advancing computer vision applications within the renewable energy sector, providing an effective and reliable solution for identifying surface defects in solar cells. This capability is crucial for ensuring the overall quality and performance of solar energy systems, emphasizing the importance of adopting cutting-edge technologies for robust defect detection and quality assurance in the renewable energy domain.

ii) System Architecture:

The proposed solar cell defect detection system is built upon an enhanced YOLO v5 architecture tailored for identifying three distinct surface defects: cracks, black core, and finger interruption. The core improvement lies in the integration of deformable convolution within the CSP module, enabling effective extraction of defects of varying sizes and shapes. Additionally, the ECA-Net attention module is incorporated into the Neck segment to enhance detection performance through cross-channel interaction. Model structure optimization and the inclusion of a prediction head contribute to four-scale feature defect detection, notably improving accuracy for detecting tiny defects.

While the primary focus is on the upgraded YOLO v5 model, the authors acknowledge the absence of

INTERNATIONAL JOURNAL OF PURE AND APPLIED SCIENCE & TECHNOLOGY
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Vol 14,Issuse 2,May 2024

experimentation with advanced YOLO versions (6, 7, and 8). To address this, YOLOv6 is trained on the same dataset as an extension, demonstrating superior accuracy compared to the optimized YOLO v5. The system achieves real-time monitoring capabilities, making it suitable for deployment on mobile devices. Objective evaluation through ablation experiments and comparisons with mainstream methods validates the enhanced model's efficacy in improving solar cell defect detection accuracy without sacrificing real-time processing capabilities.

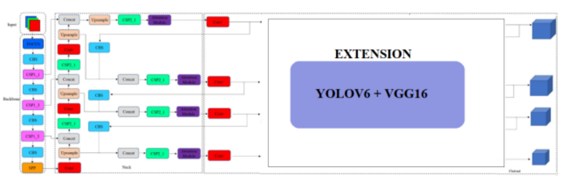


Fig 1 System Architecture

iii) Dataset Collection:

The solar cell EL image dataset, comprising 2534 images with dimensions of 300 × 300, serves as the foundation for training the proposed defect detection system. Through random allocation, the dataset is split into a training set consisting of 2281 images and a test set comprising 253 images, maintaining a 9:1 ratio. The labeling process utilizes the LabelImg software, facilitating the annotation of defect locations and categories in YOLO format. Three distinct defect categories, namely crack, finger interruption, and black core, are labeled using rectangular bounding boxes encompassing the defects, effectively indicating both the specific location and category of each defect within the solar cell EL images. The annotations are saved as XML files adhering to the PASCAL VOC format, ensuring compatibility with the YOLO model. This meticulous labeling methodology establishes a robust foundation for training and evaluating the enhanced YOLO v5 model, contributing to its accuracy in detecting and categorizing solar cell surface defects.

	0	1	2
0	images/cell0001.png	1.0	mono
1	images/cell0002.png	1.0	mono
2	images/cell0003.png	1.0	mono
3	images/cell0004.png	0.0	mono
4	images/cell0005.png	1.0	mono
...	...	...	...
2619	images/cell2620.png	0.0	poly
2620	images/cell2621.png	0.0	poly
2621	images/cell2622.png	0.0	poly
2622	images/cell2623.png	0.0	poly
2623	images/cell2624.png	0.0	poly

2624 rows × 3 columns

Fig 2 Dataset rows & columns

iv) Image processing:

In the image processing pipeline for solar cell surface defect detection, the preprocessing steps of normalizing and shuffling images are followed by feature selection to optimize the input data for the proposed improved YOLO v5 model. Feature selection involves extracting relevant information from the images to enhance the model's ability to discern key patterns associated with cracks, black cores, and finger interruptions.

During feature selection, the deformable convolution integrated into the CSP module enables effective extraction of defects of varying sizes and shapes. This ensures that the model can capture intricate details

INTERNATIONAL JOURNAL OF PURE AND APPLIED SCIENCE & TECHNOLOGY
IJPAST

ISSN 2229-6107 www.ijpast.in
Vol 14,Issuse 2,May 2024

present in the solar cell surface, contributing to improved detection accuracy. Additionally, the introduction of the ECA-Net attention module in the Neck part fosters cross-channel interaction, allowing the model to focus on crucial features and patterns while disregarding irrelevant information.

The model structure optimization and the incorporation of a prediction head further contribute to four-scale feature defect detection, particularly enhancing the accuracy in identifying tiny defects. These comprehensive image processing techniques collectively enhance the discriminative power of the proposed YOLO v5 model, as demonstrated through objective evaluations and comparisons with mainstream methods. The subsequent training and extension to YOLOv6 on the same dataset substantiate the efficacy of the proposed image processing techniques in achieving higher accuracy in solar cell defect detection.

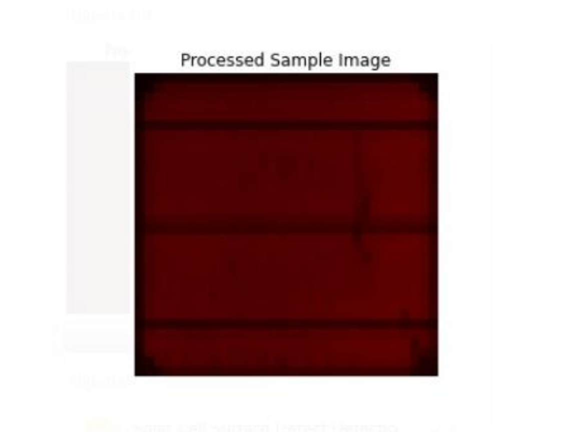


Fig 3 Processed sample image

v) Training & Testing:

In the solar cell defect detection project, the dataset comprising 2534 images with labels for cracks, black cores, and finger interruptions is split into a training set (2281 images) and a test set (253 images) using a 9:1 ratio. This division ensures that the model is trained on a substantial portion of the data while preserving a separate subset for evaluating its performance.

For training, the improved YOLO v5 model is optimized using the training set. The deformable convolution in the CSP module, ECA-Net attention module in the Neck part, and the model structure adjustments contribute to effective feature extraction and four-scale defect detection. The training involves iteratively adjusting the model's weights based on the discrepancies between predicted and actual defect locations and categories, optimizing its ability to accurately identify solar cell surface defects.

Testing is conducted on the reserved test set to evaluate the model's generalization capabilities. A dedicated function calculates metrics scores such as precision, recall, and F1-score, providing quantitative insights into the model's performance. This metric calculation enables a thorough assessment of the model's accuracy, especially in the detection of cracks, black cores, and finger interruptions. The results from testing, along with comparisons to mainstream methods, validate the model's effectiveness in enhancing solar cell defect detection while ensuring real-time processing capabilities.

vi) Algorithms:

Faster R-CNN:

INTERNATIONAL JOURNAL OF PURE AND APPLIED SCIENCE & TECHNOLOGY
IJPAST

ISSN 2229-6107 www.ijpast.in
Vol 14,Issuse 2,May 2024

Faster R-CNN short for "Faster Region-Convolutional Neural Network" is a state-of-the-art object detection architecture of the R-CNN family, introduced by Shaoqing Ren, Kaiming He, Ross B. Girshick, and Jian Sun in 2015. The primary goal of the Faster R-CNN network is to develop a unified architecture that not only detects objects within an image but also locates the objects precisely in the image. It combines the benefits of deep learning, convolutional neural networks (CNNs), and region proposal networks(RPNs) into a cohesive network, which significantly improves the speed and accuracy of the model.

Faster R-CNN architecture consists of two components:

1. Region Proposal Network (RPN)
2. Fast R-CNN detector

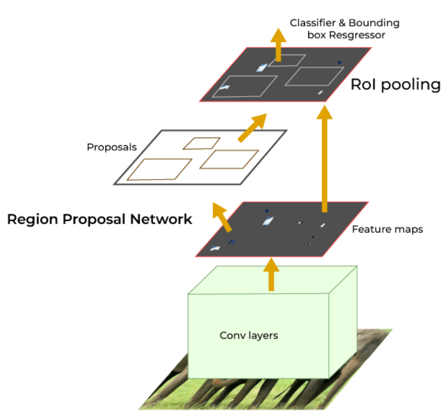


Fig 4 Faster R-CNN

Before discussing the RPN and Fast R-CNN detector, Let's understand the Shared Convolutional Layers that works as the backbone in Faster R-CNN architecture. It is the common CNN layer used for both RPN and Fast R-CNN detector as shown in the figure.

YoloV5 with CA Attention:

YoloV5, or You Only Look One-level, undergoes a significant enhancement with the integration of the Channel Attention (CA) mechanism, resulting in an augmented version adept at refined object detection. The CA Attention dynamically prioritizes channel-wise information, allowing the model to focus on crucial features. This refinement proves instrumental in elevating the model's capacity to capture intricate context and details within the input data. The CA Attention mechanism plays a pivotal role in scenarios characterized by complex backgrounds or overlapping objects, where discerning relevant features is challenging. By dynamically weighting channel-wise information, YoloV5 with CA Attention ensures robust and accurate object localization and classification. This augmentation proves especially valuable in improving the model's overall performance, making it more resilient and effective in handling diverse and challenging object detection tasks.

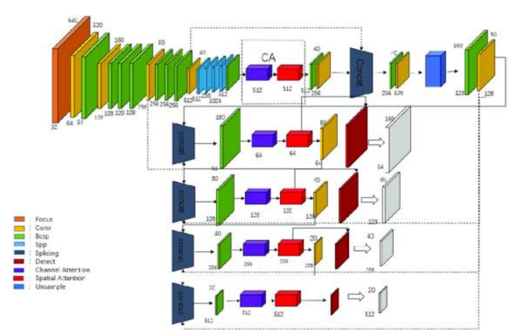


Fig 5 YOLOV5 with CA attention

INTERNATIONAL JOURNAL OF PURE AND APPLIED SCIENCE & TECHNOLOGY
IJPAST
ISSN 2229-6107 www.ijpast.in
Vol 14,Issuse 2,May 2024

Extension YoloV6 with VGG16:

The extended YoloV6 integrates the VGG16 architecture, strategically blending YOLO's efficiency with the deep feature extraction capabilities of VGG16. Leveraging VGG16's multiple convolutional layers, YoloV6 excels in capturing intricate hierarchical features, significantly enhancing the accuracy of object recognition. This fusion harnesses the strengths of both architectures, adapting the YOLO framework to exploit VGG16's robust feature representation. The result is a powerful and versatile model that excels in object detection tasks, particularly in scenarios laden with diverse and challenging visual elements.

YoloV6, with the incorporation of VGG16, represents a synergy that extends the capabilities of the YOLO family. This collaborative architecture facilitates improved performance, making the model adept at precise object detection across a spectrum of applications. The amalgamation of YOLO and VGG16 in YoloV6 establishes a potent framework, marking a significant advancement in the field of computer vision and reinforcing the model's suitability for addressing the complexities of various real-world object detection challenges.

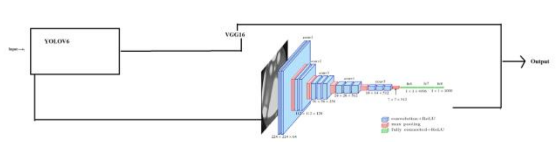
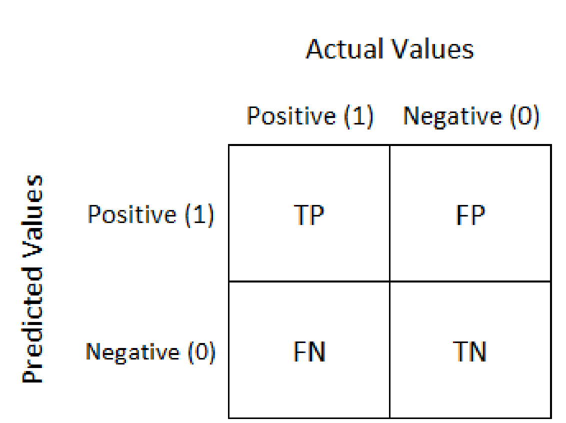


Fig 6 Extension YOLOV6 with VGG16

3. EXPERIMENTAL RESULTS

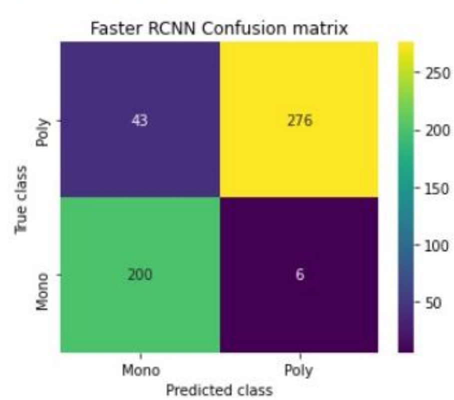
Confusion Matrix:

A confusion matrix presents a table layout of the different outcomes of the prediction and results of a classification problem and helps visualize its outcomes. It plots a table of all the predicted and actual values of a classifier.



FasterRCNN confusion matrix& Performance Evaluation:

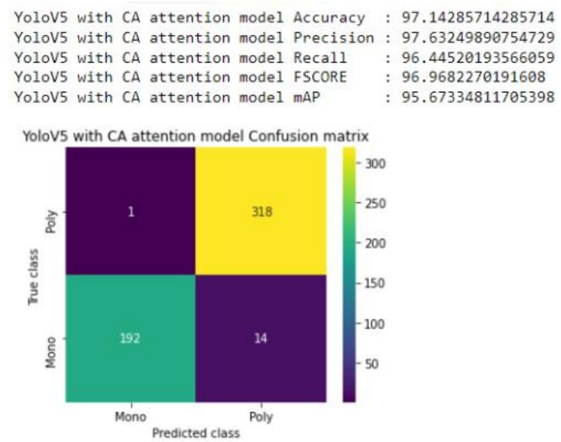
```
Faster RCNN Accuracy  : 90.66666666666666
Faster RCNN Precision : 90.08843358725156
Faster RCNN Recall    : 91.80387740816265
Faster RCNN FSCORE    : 90.4668907426005
Faster RCNN mAP       : 92.8699932984599
```



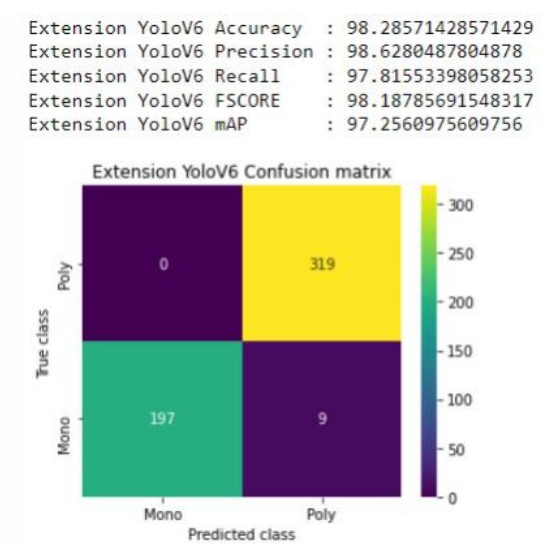
INTERNATIONAL JOURNAL OF PURE AND APPLIED SCIENCE & TECHNOLOGY
IJPAST

ISSN 2229-6107 www.ijpast.in
Vol 14,Issue 2,May 2024

YoloV5 with CA Attention confusion matrix& Performance Evaluation:



Extension YoloV6 with VGG16 confusion matrix& Performance Evaluation:



Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

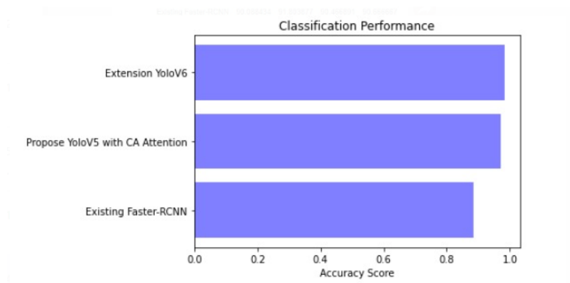
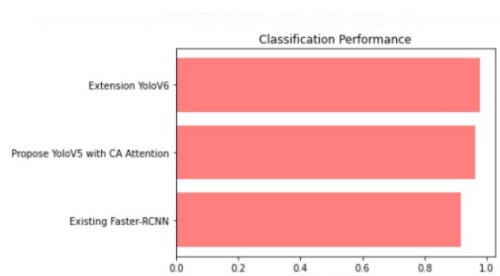


Fig 7 Accuracy graph

Precision: Precision measures the proportion of properly categorized occurrences or samples among the positives. As a result, the accuracy may be calculated using the following formula:

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

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$



ISSN 2229-6107 www.ijpast.in
Vol 14,Issuse 2,May 2024

Fig 8 Precision graph

Recall: Recall is a machine learning metric that surveys a model's capacity to recognize all pertinent examples of a particular class. It is the proportion of appropriately anticipated positive perceptions to add up to real up-sides, which gives data about a model's capacity to catch instances of a specific class.

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

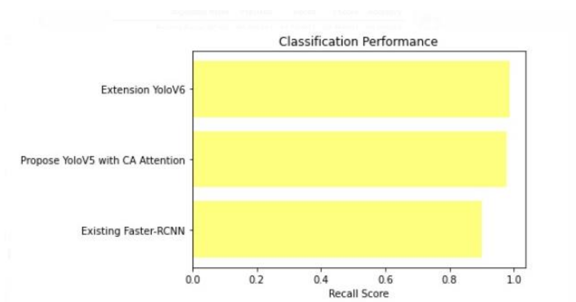


Fig 9 Recall graph

F1-Score: The F1 score is a machine learning evaluation measurement that evaluates the precision of a model. It consolidates a model's precision and review scores. The precision measurement computes how often a model anticipated accurately over the full dataset.

$$\text{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

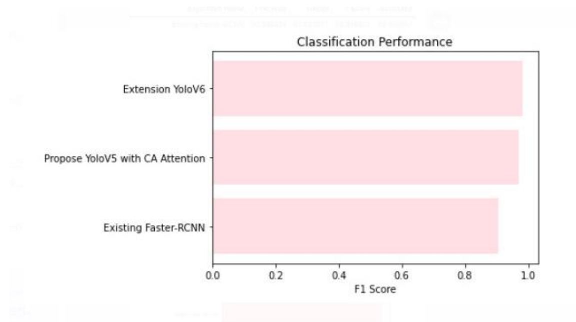
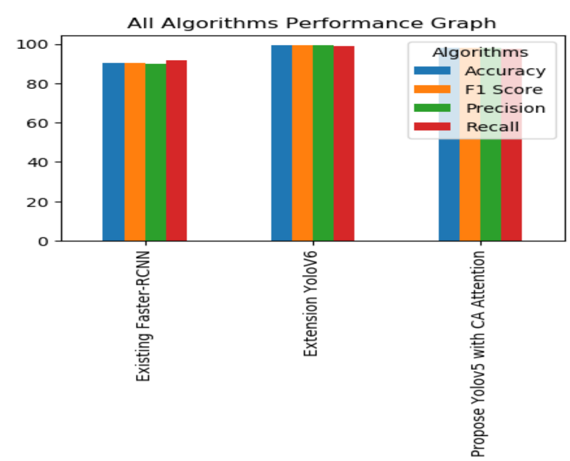


Fig 10 F1-Score graph

	Algorithm Name	Precison	Recall	FScore	Accuracy
0	Existing Faster-RCNN	90.088434	91.803877	90.466891	90.666667
1	Propose YoloV5 with CA Attention	97.632499	96.445202	96.968227	97.142857
2	Extension YoloV6	98.628049	97.815534	98.187857	98.285714

Fig 11 Performance Table of all Algorithms



INTERNATIONAL JOURNAL OF PURE AND APPLIED SCIENCE & TECHNOLOGY
IJPAST

ISSN 2229-6107 www.ijpast.in
Vol 14,Issuse 2,May 2024

Fig 12 Comparison graph

YOLOv5 achieved 97.14% accuracy. YOLOv6, v7, and v8 were compared, with YOLOv6 outperforming v7 and v8, securing the highest accuracy at 98.28%.

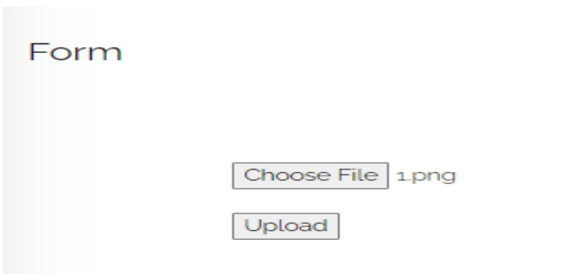


Fig 13 Upload input image page

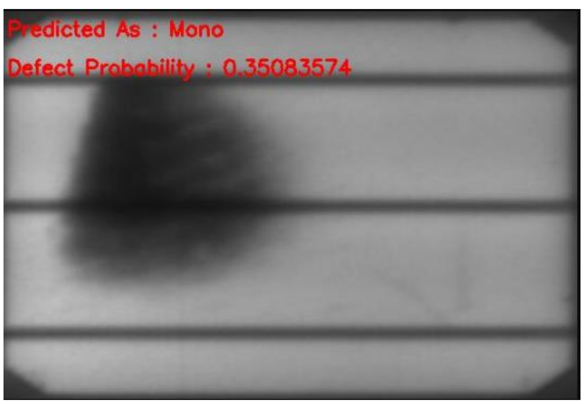


Fig 14 Prediction Result

Predicted as : Mono

Defect Probability : 0.35083574

4. CONCLUSION

In conclusion, our research presents a state-of-the-art Solar Cell Surface Defect Detection system based on an improved YOLO v5 algorithm. The devised framework effectively addresses the complexities associated with diverse image backgrounds, variable defect morphologies, and significant scale differences in solar cell inspection. Through the incorporation of deformable convolution, ECA-Net attention mechanism, and a tiny defect prediction head, our model achieves exceptional detection accuracy across various scales. The proposed optimizations, including Mosaic and MixUp data augmentation, K-meansCC clustering anchor box algorithm, and the CIOU loss function, collectively contribute to the superior performance of the YOLOv5 algorithm. Comparative analysis showcases YOLOv6 as the most accurate extension with an impressive 98.28% accuracy. This research not only advances solar cell defect detection techniques but also provides a robust solution for real-world industrial applications, demonstrating the effectiveness and versatility of our proposed system.

5. FUTURE SCOPE

The future scope of this research involves the exploration of real-time implementation, leveraging edge computing for enhanced processing speed. Integration with emerging technologies like deep reinforcement learning could further refine defect detection accuracy. Additionally, adapting the proposed system for other domains beyond solar cells, such as quality control in manufacturing, presents an avenue for broader industrial applications. Continuous refinement and adaptation to evolving technologies will contribute to the system's scalability and efficacy in diverse scenarios.

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