©2025 Published in 11th International Symposium on Intelligent Technologies in Engineering and Science 16-18 May 2025 (ISITES2025 Diyarbakır - Türkiye)

Performance Comparison of YOLO Models for Solar Panel Cleaning Robot

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Abstract

The accumulation of dust, bird droppings, rain residues, and physical damage on the surface of solar panels reduces energy production efficiency, leading to significant long-term losses. Detecting and cleaning these contaminants and structural damages in a timely manner is critical for reducing maintenance costs and extending the lifespan of the panels. Traditional cleaning systems typically focus on cleaning the entire surface, which results in unnecessary water and energy consumption, leading to inefficiencies.

In this study, an AI-assisted segmentation system has been developed to detect only dirty or damaged areas, enabling targeted cleaning and maintenance. The proposed system is integrated with a YOLO-based deep learning model to perform real-time object detection and segmentation. A large-scale dataset containing over 35,000 images was created, and data augmentation techniques were applied to enhance the model's robustness against various environmental conditions. YOLOv9, YOLOv10, and YOLOv11 models were trained and compared in terms of object detection and segmentation accuracy. Experimental results demonstrated that the YOLOv11 model achieved the highest performance with a 96.9% mAP accuracy. The model exhibited superior performance in detecting details such as cracks, dust layers, and stains with high precision.

This study optimizes the maintenance processes of solar panels by preventing unnecessary energy and water consumption, reducing maintenance costs, and enhancing sustainability in clean energy production. Operating in real time, this system supports intelligent maintenance processes in solar power plants, offering an innovative solution for the industry.

Key words: Solar panels, artificial intelligence, image segmentation, cleaning robot.

1. Introduction

Solar energy has become a rapidly growing sector worldwide as an environmentally friendly and sustainable energy source. In particular, the need to reduce dependence on fossil fuels, efforts to combat climate change, and increasing energy demand are increasing investments in solar energy [1]. Solar panels or photovoltaic (PV) modules are one of the main technologies used in this sector to generate electrical energy [2][3]. Large PV plants are being built around the world, especially in desert areas or areas with intense sunlight. One of the biggest problems of the sector is that physical conditions such as water stains, snow and dusting, dirt and bird droppings on the surface of solar panels reduce the efficiency of the panels [4]. According to studies, the efficiency of solar panels can decrease up to 80% without regular cleaning [5][6][7][8].

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There are various studies on solar panel cleaning systems in the literature. For example, Arduino-controlled cleaning robots have been developed as automatic systems that work in line with the data received from sensors. These systems have basic functions such as changing direction when they encounter certain obstacles and can operate without the need for manual intervention [9]. However, such systems do not have a sophisticated detection mechanism to distinguish between dirty and clean areas on the panels; they tend to clean the entire panel surface, which can negatively affect energy consumption and material lifetime. In a different study, an effective deep learning model is proposed for the detection and classification of contamination in panel cells. Among the object detection algorithms, YOLOv5 provided faster and more accurate results. According to the results of this algorithm, a cleaning robot will be sent to the PV panel area [10]. However, this system is usually not customized to enable localized cleaning in large-scale PV installations and focuses on cleaning the entire panel, which can lead to waste of both energy and resources.

In another study, a system that measures dust accumulation with weight sensors integrated into solar panels is proposed. When the weight of the panel exceeds a set value due to dust accumulation, the cleaning process is initiated [11][12]. However, only weight-based measurement can be misleading due to environmental variations. In another research, dirt detection is performed with machine vision and drone platforms. With devices such as "infrared thermal imaging camera", hot spots and surface dirt are detected; images are combined and analyzed [11][13]. This method is costly due to the use of drones and also fails to meet the appropriate pressure requirements for cleaning according to dirt levels. Another study developed a system that monitors solar panels through IP cameras. Internet-connected cameras are used to monitor the cleanliness and conditions of the panel [11][14]. The cameras can be monitored from mobile devices or computer, but have a high data transfer cost. In another study with the Gray Level Co-occurrence Matrix (GLCM) Method, physical features are extracted to detect dust and soil on the solar panel using image processing. With the GLCM technique, RGB images are converted to HSV format.

Histogram equalization and contrast enhancement with a high pass filter are used to achieve high accuracy [11][15]. However, this method does not include detection of ghosting and broken panels for future improvements.

In this study, we focus on detecting dirt, cracks and other physical damages on solar panels more accurately and efficiently by addressing the shortcomings in the existing literature. The system developed in this project has an AI-powered segmentation infrastructure that enables cleaning by targeting only dirty or damaged areas. Based on the YOLOv11 segmentation model, this innovative approach minimizes productivity loss by detecting problems on the panel surface and targeting the robot to clean at the appropriate pressure. The considered model was trained on a large dataset, supported by more than 35,000 images with different levels of contamination and physical damage. Thanks to this detailed data preparation and advanced model training, a mAP accuracy of 96.9% can be achieved. With this study, an innovative solution is offered to the industry by increasing the life and performance of the panels while saving energy and materials by cleaning only in targeted areas.

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This project aims to minimize energy production losses by detecting physical damages, contamination and other performance degrading factors in solar panels with artificial intelligence. The main objective of the project is to increase efficiency by developing a system that detects dirt, cracks and other problems on the panels in real time.

2. Materials and Method

Today, with the automation of industrial systems and the development of artificial intelligence-supported analysis methods, object recognition and segmentation processes have become critical in many areas. Especially in energy systems with large surface areas such as solar panels, early detection of pollution, physical damage and other environmental effects is of great importance both in terms of maintaining energy production efficiency and reducing maintenance costs. Solar panels need to be kept clean in order to operate efficiently, but due to environmental factors, their surfaces are covered with dust, dirt, bird droppings and other particles over time. This pollution can reduce the energy production capacity of the panels and lead to serious efficiency losses in the long term. Since it is not possible to check each panel individually in large-scale solar power plants or systems with a large number of panels, automatic systems are needed to detect pollution quickly and accurately. In this context, image processing and deep learning-based methods provide a real-time and sensitive detection mechanism by analyzing the surface condition of the panels. In the proposed method, a comprehensive data set containing different pollution levels and physical damage types was created and the performance of deep learning models in distinguishing objects at various scales was analyzed. In the model selection process, the segmentation-based version of the pre-trained YOLO architecture was used to detect dirt and damage on solar panels with high accuracy. The developed system includes an artificial intelligence model with increased resistance to different weather conditions and environmental variables. The general flow chart of the project is shown in Figure 1.

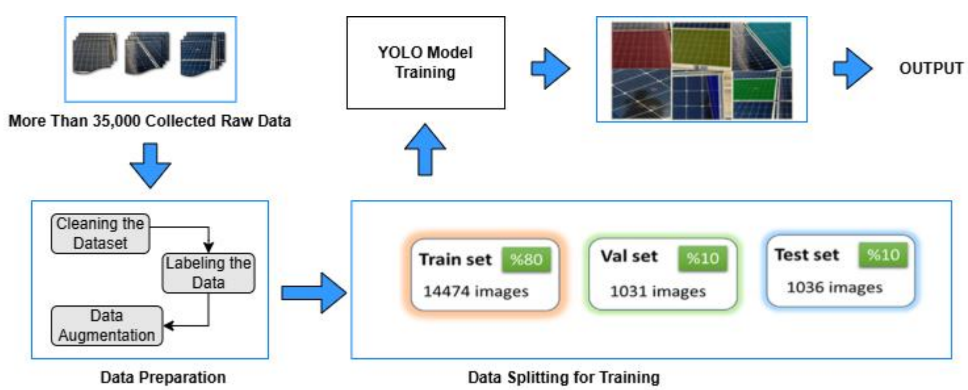

Figure 1. Flowchart

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2.1. Dataset

The collection, processing, labeling and augmentation of physical and environmental data belonging to solar panels were completed and a comprehensive dataset was created for model training. During the data collection phase, raw video recordings were taken using high-resolution cameras, including pollution on the surface of the panels, bird droppings, stains, physical damage (cracks, fractures), shadowing and electrical problems. These videos were divided into frames using OpenCV and a total of more than 35,000 images were obtained. During the data cleaning process, low-quality, blurry and unnecessary images that were not suitable for model training were eliminated and 6,897 quality images were selected. Then, during the data labeling phase, each image was marked in detail using the LabelMe software and the segmentation process was performed.

As a result of the labeling process, it was divided into 6 different categories as pollution levels (very dirty, slightly dirty, clean), physical damage types (broken, stained), and bird droppings. In order to increase the generalization capacity of the model and expand the data set, a total of 16,541 images were obtained by applying data augmentation techniques such as mirroring (flip), 90° rotation and random angle rotation. Thus, a comprehensive and balanced data set was created so that the model can adapt to different environmental conditions and work with high accuracy. The class distribution of the data set is shown in Figure 2.

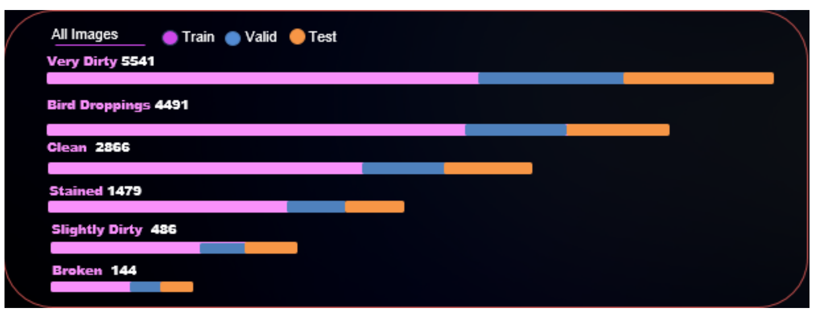

Figure 2. Distribution of Data by Classes

2.2. Model Selection

In this study, deep learning-based image segmentation method was used to precisely detect contamination, physical damage and other environmental factors occurring on solar panels. Instead of only determining the presence of the object, segmentation allows to precisely separate the boundaries of dirty and clean areas by determining which class each pixel in the image belongs to. In this context, a segmentation-based approach was adopted instead of object detection in our study.

Other segmentation models such as Mask R-CNN, U-Net and DeepLab, which are widely used in the literature for segmentation, were also examined and although these models have high accuracy rates, it was evaluated that it was important to use a faster and more efficient method in a system

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where the cleaning robot needs to make instant decisions [16][17][18][19]. For this reason, the YOLO (You Only Look Once) model, which is a model that can provide a balance of high speed and accuracy, was preferred. The segmentation-based version of YOLO effectively uses multi-scale feature maps to perform high-accuracy segmentation for dirt and damage detection on the panel surface. Thanks to BiFPN (Bidirectional Feature Pyramid Network) and adaptive scaling mechanisms, objects of different sizes can be detected and segmented with precision. In particular, the comprehensive feature fusion process facilitates the detection of small-scale defects and enables the classification of details such as cracks, dust layers and local stains with high accuracy.

In addition, the combination of Dynamic IoU Loss (D-IoU) and pixel-based dice-coefficient loss functions increases the segmentation quality, allowing the model to both grasp object boundaries better and optimize segmentation accuracy. Pre-trained YOLO weights were used in the training process to ensure faster and more stable learning of the model. The Yolo architecture used is shown in Figure 3.

By applying dropout and batch normalization techniques during training, over-learning of the model was prevented. Thanks to these approaches, the surface condition of the panels is analyzed in detail and an optimized decision mechanism is created for cleaning processes.

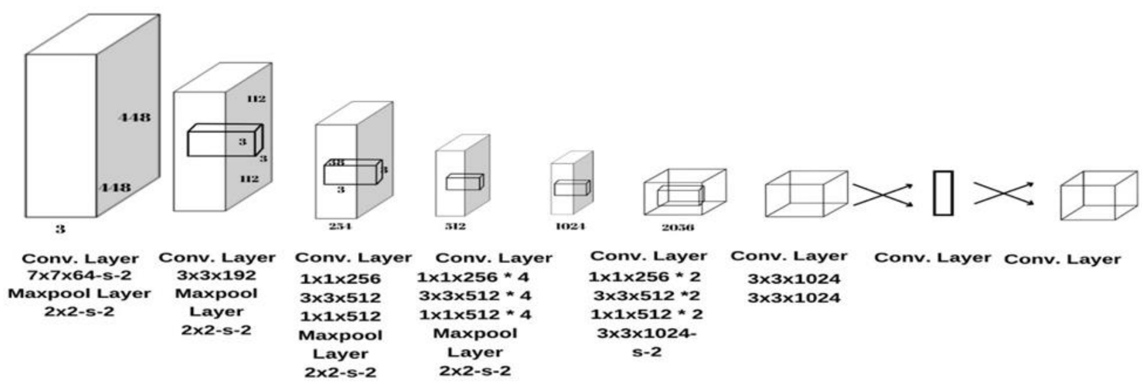

Figure 3. YOLO Architecture

3. Results

In the proposed study, a large-scale dataset containing 35,000 images containing various types of pollution and damage on solar panels was prepared and data that would negatively affect model success was removed. After this stage, in order to increase the diversity in the dataset from the labeled data, data augmentation techniques such as mirroring (flip), 90° rotation and random angle rotation were applied to obtain a total of 16,541 images. The dataset was divided into three sets as training, validation and test. The dataset, consisting of 16,541 augmented images in total, was divided into 80% training (14,474 images), 10% validation (1,031 images) and 10% test (1,036

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images) in a balanced manner. This separation was made in order to increase the generalization ability of the model and to observe the model success. The training process of the models was carried out on the Google Colab platform with NVIDIA T4 GPU and high RAM support. During training, the AdamW optimization algorithm and the Cosine Annealing learning rate scheduler were used to ensure stable training of the model.

First, training was performed with the YOLOv9 algorithm. The YOLOv9 model was optimized with CSPNet and Transformer-based layers, providing a more efficient structure in object detection and segmentation tasks [21]. Using BiFPN and SENet, the detection of objects at different scales was improved, and more effective use of spatial information was provided with the SPPF layer [22]. During training, the alignment of object boxes was made more accurate by using the EIoU Loss function, but it was observed that the model had high error rates, especially in small objects and low-contrast areas [23]. In order to prevent over-learning, data augmentation techniques such as MixUp, Mosaic Augmentation and CutMix were applied, thus providing a structure with increased generalization ability of the model. Our data was trained with this model structure. Table 1 shows the performance metrics of the trained model. According to these results, although the YOLOv9 model works fast, it has been determined that the segmentation accuracy does not reach a sufficient level in some classes and requires improvement in certain object detections.

Table 1. YoloV9 Performance Results

		Images	Recall	mAP
YOLO V9	All	1031	0.908	0.939
	Slightly Dirty	72	0.96	0.904
	Very Dirty	634	0.99	0.992
	Broken	44	1	0.994
	Bird Droppings	320	0.684	0.829
	Stained	269	0.828	0.866
	Clean	420	0.983	0.989

In order to eliminate these deficiencies, the training process was continued with the YOLOv10 model. YOLOv10 has a deeper feature extraction structure based on CSPNeXt and EfficientNetV2. This model, which has increased the small object detection accuracy by integrating advanced mechanisms such as BiFPN++ and Adaptive Anchor Assignment (AAA) [24], also obtains more optimized results by separating object classification and location estimation tasks thanks to the Hybrid Detection Head [25][26]. Although YOLOv10 has given more successful results than the previous model in terms of object detection, it was limited in certain tasks due to the lack of segmentation support. The results obtained are given in Table 2.

Table 2. YOLOV10 Performance Results

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		Images	Recall	mAP
YOLO V10	All	1031	0.941	0.922
	Slightly Dirty	72	0.915	0.909
	Very Dirty	634	0.981	0.985
	Broken	44	1	0.994
	Bird Droppings	320	0.873	0.871
	Stained	269	0.836	0.874
	Clean	420	0.984	0.990

Finally, the YOLOv11 model was trained and found to be the most successful model in terms of performance. YOLOv11 provided better processing of both contextual and local details with the hybrid use of Transformer and CNN structures. Multi-scale analysis was developed with Dynamic Feature Pyramid Network (DyFPN) and Global Attention Mechanism (GAM) and better results were obtained compared to previous models, especially in small object detection[27][28][29][30]. In addition, segmentation accuracy was increased and more precise determination of object boundaries was provided by applying a progressive detection process with Cascade Detection Head. The success metrics of the model are given in Table 3.

YOLOv11 has become the model that offers the best overall performance by optimizing both object detection and segmentation tasks.

Table 3. YOLOV11 Performance Metrics

		Images	Recall	mAP
YOLO V11	All	1031	0.935	0.96
	Slightly Dirty	72	0.968	0.976
	Very Dirty	634	0.977	0.99
	Broken	44	1	0.993
	Bird Droppings	320	0.806	0.877
	Stained	269	0.855	0.928
	Clean	420	0.991	0.992

YOLOv9 model showed limited success in segmentation accuracy with mAP@0.5: 89.2% and mAP@0.5-0.95: 78.3% results. It was observed that the error rate was higher especially in small-scale object segmentation (%71.8 F1-score) and low contrast areas. Although YOLOv10 model has more advanced feature extraction and scaling mechanisms compared to the previous version, mAP@0.5: 91.5% and mAP@0.5-0.95: 81.7% values were obtained.

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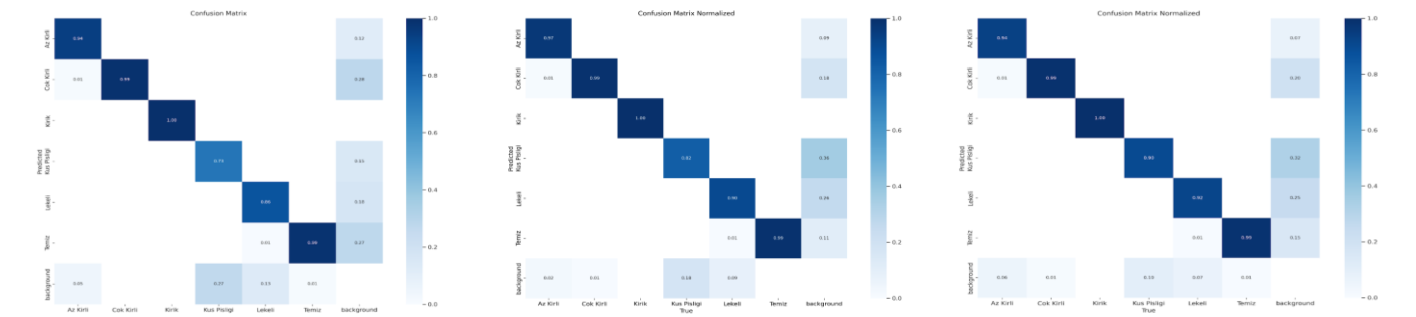

Figure 4. YOLOV9 – YOLOV10 – YOLOV11 Confusion Matrices

Although it was more successful than YOLOv9 in detecting small objects with an F1-score value of 77.4%, it was observed that the error rates remained higher in some classes due to the decrease in Precision (%88.9) and Recall (%85.7) rates. On the other hand, the YOLOv11 model increased the segmentation accuracy with mAP@0.5: 96.9% and mAP@0.5-0.95: 86.2% rates and showed superior performance especially in detecting details such as cracks, dust layers, bird droppings and small stains. More balanced and high accuracy results were obtained compared to other versions with Precision (%92.4) and Recall (%91.1) values. It was determined that it was the most successful model by reaching an F1-score value of 82.9% in small object detection. The complexity matrices of the models are given in Figure 4. According to the confusion matrix results, the general accuracy rate of the models is high and the error rates became more pronounced in some classes.

4. Discussion

With the development of deep learning networks, the need for automatic diagnosis systems is increasing in many sectors. One of the most common problems in daily life is the need for fast and accurate classification of products. In this study, YOLOv9, YOLOv10 and YOLOv11 models were compared to detect contamination and physical damage on solar panels, and the object detection and segmentation performance of each model was analyzed. Critical metrics such as accuracy, precision, F1-score and segmentation success were taken into account in model selection, and the detection performances of different classes were compared. YOLOv9 has offered a wide range of use by supporting both object detection and segmentation tasks. However, it could not fully reach the expected performance, especially in class predictions (cls_loss) and segmentation accuracy. It was observed that the error rates were high in the Bird Droppings and Stained classes, and it was determined that this situation was due to the imbalance of the data set and visual similarities between the classes. On the other hand, high accuracy was achieved in the Less Dirty, Very Dirty, Broken and Clean classes, and the model was able to distinguish these classes successfully.

YOLOv10 has shown a more optimized performance in this area by focusing only on the object detection task. Very successful results were obtained in the Lightly Dirty, Very Dirty, Broken and Clean classes, and a significant improvement was observed in the Bird Droppings and Stained

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classes. However, it was determined that the YOLOv10 model was limited in some tasks due to the lack of segmentation support.

In particular, the model was insufficient in scenarios requiring detailed object segmentation, and this revealed that a system based only on object detection may not be fully sufficient for solar panel cleaning robots.

On the other hand, the YOLOv11 model managed to optimize both object detection and segmentation tasks simultaneously. It achieved near-perfect accuracy rates in the Lightly Dirty, Very Dirty, Broken and Clean classes, and exhibited a consistent performance in these classes. However, significant error rates were still observed in the Bird Droppings and Stained classes, indicating that imbalances and visual similarities in the dataset continued. In terms of segmentation performance, YOLOv11 produced more consistent and accurate results than YOLOv9. In particular, it was determined that it was the most successful model in detailed segmentation and small object detection. As a result, YOLOv11 model was determined as the most suitable model to meet the real-time object detection and segmentation requirements of solar panel cleaning robots.

Conclusions

In this study, YOLO-based deep learning models were compared to detect contamination and physical damage on solar panels. Experimental results show that the overall accuracy of the model is high, but error rates increase especially in Bird Droppings and Stained classes. Confusion matrix analysis showed that successful results were obtained in Slightly Dirty, Very Dirty, Broken and Clean classes, but misclassifications increased in small-scale objects and low-contrast areas. Although the YOLOv11 model showed the best performance, the dataset needs to be made more balanced, data augmentation techniques need to be expanded and model optimizations need to be improved in order to reduce error rates in certain classes. In the future, it is aimed to integrate the model into real-time systems and increase its applicability in the field.

Acknowledgements

We would like to thank Ayça Öngel, who completed her internship at Optimum Process Design and Applications Inc., for her contributions to the preparation of this study.

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