

Visual Dust Detection on Solar Photovoltaic Panels Using Convolutional Neural Networks

Emre Ayik¹, Hakan Isik², Yavuz Selim Taspinar³

¹Department of Electric Electronic Engineering, Faculty of Technology Selcuk University, Konya, TURKIYE

²Department of Electric Electronic Engineering, Faculty of Technology Selcuk University, Konya, TURKIYE

³Department of Mechatronic Engineering, Faculty of Technology Selcuk University, Konya, TURKIYE

Corresponding Author: Yavuz Selim Taspinar

Abstract

Solar energy distinguishes itself within the spectrum of renewable resources through its inherent sustainability and environmental compatibility. Nevertheless, the progressive accumulation of dust on photovoltaic surfaces hampers light transmittance, thereby leading to a substantial decline in power generation performance. Therefore, determining the need for cleaning the panels at the right time is of critical importance in terms of reducing maintenance costs and ensuring maximum efficiency. In this study, a classification system was developed using image processing and deep learning methods in order to detect dust accumulation, which negatively affects efficiency in solar energy production. Using the “Solar Photovoltaics Panel for Dust Detection” dataset, a total of 842 images labeled as “clean” and “dirty” were evaluated. These images were classified with deep learning-based SqueezeNet, VGG16 and VGG19 models and their performances were compared. According to the experimental results, the VGG19 model showed the highest success with 98.3% accuracy rate, 0.980 precision, 0.992 recall and 0.986 F1 Score values. The findings have shown that CNN-based approaches are effective in solar panel surface condition analysis. In addition, this study has made a significant contribution to the usability of image-based automatic dust detection systems in panel maintenance processes. The limitations of the study include the lack of data diversity and lack of integration into real-time applications. In future studies, it is aimed to increase the generalization success of the model with larger data sets that include real field conditions and to integrate it into mobile surveillance systems.

Keywords: tyre, defective, forecasting, cnn, vehicle

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I. INTRODUCTION

The accumulation of dust, dirt, bird droppings, pollen, and other environmental contaminants on the surface of solar panels over time hinders the effective transmission of solar irradiance to the panel surface, thereby leading to direct losses in the energy production performance of photovoltaic (PV) systems. This accumulation makes it difficult for sunlight to reach the cells and reduces light transmittance. As a result, energy production can decrease by up to 20%, and this loss can cause serious economic losses in large-scale solar energy fields. Therefore, keeping solar panels clean is essential to maintain energy production at maximum levels. Nevertheless, the manual cleaning of solar panels is a labor-intensive, time-consuming, and cost-inefficient process. In particular, the regular and sustainable cleaning of panels in large-scale solar power plants distributed over extensive areas poses significant logistical challenges. In addition, environmental impacts such as water usage should be taken into account during this cleaning process. For this reason, it is necessary to develop more efficient, sustainable and low-cost solutions. At this point, image processing technologies can come into play and make significant contributions to the optimization of cleaning processes. Image processing offers an effective method for continuous monitoring of solar panel surfaces and detection of contamination levels. Advanced image processing algorithms can automatically identify contaminated areas by analyzing high-resolution images obtained by drones or fixed cameras. This system detects the dust and dirt layer accumulated on the panels based on various visual cues, such as specific color changes, brightness differences or textural features. By analyzing the amount and distribution of contamination on the surface, only the areas that need to be cleaned are identified, thus enabling targeted cleaning. This approach offers great advantages in terms of both time and cost. Selbaş and Çetin conducted a detailed investigation into the system-related and environmental factors associated with

photovoltaic panels that determine the performance of a photovoltaic power plant. Within this scope, the key parameters influencing the efficiency of solar panels were analyzed. Furthermore, thermal analyses and current-voltage (I-V) characteristics were evaluated to assess the impact of shading, physical degradation, and thermal losses on the overall system performance. They examined the current-voltage curves of the panels by making on-site measurements according to IEC standards. They compared the measured values with the data in STC and examined how the panel performance was affected and how this situation affected the photovoltaic plant, and observed the changes in performance values with the help of the graphs created [1]. Yuliya et al. studied the performance of solar panels that were polluted in Russia. They conducted the study under laboratory conditions. During the study, they noted that in the cities of Azov, Novokuznetsk, Lipetsk, Magnitogorsk, Volgograd, Norilsk, Nizhnekamsk and Chita in Russia, the pollution on the panels would be higher than in other cities due to the industrial sector. They stated that it would be more efficient to install solar panels in the southern regions, except for the areas where industry is developed and construction is ongoing. In addition, the North Caucasus, the Republic of Crimea, the Vladivostok region, and the south of Western and Eastern Siberia were determined as suitable regions for solar panels [2]. In the study conducted by Kalász and Bodnár, the heating effects occurring in solar panels and their adverse implications for energy production were examined in detail. Prolonged operation under elevated temperature conditions may lead to the degradation of the crystal structure of solar cells, particularly in hot-spot regions. Electroluminescence (EL) imaging and thermal measurement data confirm the presence of such crystal structure failures. Moreover, in addition to structural deformation and accelerated aging of solar cells, environmental pollutants have been reported to cause power losses reaching up to 10% [3]. In the study conducted by Öztürk et al., a portable and low-cost solar panel cleaning robot equipped with a dust-blowing function was designed and manufactured with the aim of minimizing labor costs. The developed system offers several advantages, including high service efficiency, an environmentally friendly design, energy-independent operation, autonomous functionality, long operational lifespan, and cost-effectiveness. Measurements performed after the cleaning process indicated an increase of 8.02% in the output voltage and 18.78% in the output current of the solar panel. Furthermore, image processing analyses were carried out by classifying surface color variations of the solar panel using images captured by a camera mounted on the robot [4]. Lermi and Onur performed damage detection classification on solar panels using deep learning technique. The study consists of two stages. The first stage is the preprocessing stage. Since the data set is insufficient at this stage, they increased the data set using data augmentation techniques. In the second stage, the training stage, the replicated data set is trained with the proposed deep learning model. As a result of the training, they observed that the proposed model achieved 96.56% success in classifying 7 different faults [5]. In the study conducted by Yap and Galet, a comprehensive image processing toolbox was developed to assess dust accumulation and fouling on photovoltaic panels. The proposed toolbox integrates multiple techniques, including threshold-based binarization methods, histogram and statistical modeling approaches, as well as image and texture matching algorithms. The performance of the methodology was evaluated using both controlled-condition images and real-world field images, yielding mean error rates of 12.38% and 10.8%, respectively. The analysis demonstrated that the binarization algorithm provided the fastest and most accurate results under controlled imaging conditions, whereas the image matching algorithm achieved the highest accuracy when applied to real-world images. Furthermore, the study confirmed that the proposed approach offers high accuracy, low implementation cost, and ease of deployment, while critically providing end users with essential decision-support information to maintain photovoltaic system efficiency throughout the wet and dry seasons in Northern Australia [6]. In the experimental study conducted by Kaldellis et al., the effects of Total Suspended Particulates (TSP) accumulation on the performance of photovoltaic panels operating in urban environments were examined in detail. Given that dust accumulation is a site-specific phenomenon, the investigation was carried out under the dense and highly polluted urban conditions of Athens, the capital of Greece. Within this framework, the performance of a pair of PV panels exposed to natural air pollution for a defined period was comparatively evaluated against an identical panel pair maintained under clean conditions. The findings revealed that even a short-term exposure to open-air conditions without cleaning (approximately one month) resulted in a noticeable deterioration in PV panel performance, corresponding to an absolute efficiency reduction of 0.4% due to dust accumulation [7]. In the study conducted by Onim et al., a comprehensive dataset consisting of images of clean and dust-covered solar panels was constructed and evaluated using state-of-the-art (SOTA) classification algorithms. Subsequently, a novel convolutional neural network (CNN) architecture, termed SolNet, was proposed with a specific focus on detecting dust accumulation on solar panel surfaces. A detailed comparative performance analysis was carried out between the proposed SolNet model and existing SOTA algorithms. The results demonstrated that SolNet outperformed the benchmark methods, achieving a classification accuracy of 98.2% [8]. In the study conducted by Myyas et al., an innovative smart device with multifunctional capabilities was developed to enhance the efficiency of solar cells through an integrated self-cleaning mechanism. The proposed system not only prevents excessive temperature rise in solar cells but also recycles cleaning water and collects rainwater, thereby providing a sustainable solution. The experimental implementation was carried out on photovoltaic panels installed on the roof of the Najashi Mosque located in Salt

City, Jordan. To ensure regular removal of dust accumulation on the panel surface, an automated system capable of detecting dust presence and autonomously cleaning the panel modules was deployed. Furthermore, the performance of various cleaning approaches, including manual cleaning, automatic cleaning, manual water spraying, and compressed air cleaning, was comparatively evaluated [9].

II. MATERIAL AND METHODS

2.1. Convolutional Neural Network (CNN)

Convolutional neural networks (CNNs) are one of the cornerstones of deep learning methods, and have achieved significant success in areas such as image processing and classification. These networks were developed by taking inspiration from the biological vision system and mimic the functioning of the visual cortex in the human brain [10]. CNNs are specifically capable of learning spatial hierarchies through convolutional filters arranged in layers. These filters automatically detect edges, textures, and other features in images, transforming raw data into more complex and meaningful feature representations [11]. CNNs exhibit high performance, especially when working on large datasets. This performance reinforces their applicability to various data types and their success in different fields, despite the high computational power required by CNNs. Advanced CNN architectures such as ResNet [12], VGGNet [13] and Inception [14] have demonstrated superior performance on more complex tasks by increasing the depth and breadth of the networks. Moreover, CNNs are not limited to image processing but are also used in various fields such as natural language processing, voice recognition and biomedical signal processing [15].

2.2. VGG16

The VGG16 architecture is a well-established convolutional neural network model widely employed in deep learning, particularly for image classification tasks. The model is characterized by a hierarchical structure composed of multiple consecutive convolutional layers followed by pooling layers. VGG16 comprises a total of 16 trainable weight layers, including 13 convolutional layers and 3 fully connected layers. Owing to this architectural design, the network progressively learns feature representations, starting from low-level visual patterns such as edges and textures and advancing toward more complex, high-level semantic features [16]. One of the features of VGG16 is the use of a fixed and small filter size (3x3) for all convolutional layers. This approach allows learning features in a wider area, while at the same time increasing the depth of the model and keeping the number of parameters at a manageable level. Such an architecture increases the learning capacity of the model, but also significantly increases its computational complexity [13]. The model contains 138 million parameters in total, which results in high memory requirements and therefore VGG16 is considered a difficult model to train on large datasets [17].

2.3. VGG19

VGG19 is a convolutional neural network model widely used in deep learning and computer vision. This model consists of 19 layers and contains 16 convolutional layers, each with small filters of 3x3 size. This structure increases the total number of parameters of the model while improving its capacity to learn complex features of images [18]. The deep architectural structure of VGG19, together with its systematic inter-layer connections, contributes to achieving high accuracy performance, particularly in high-volume image classification problems [19]. Despite its relatively simple architectural design, VGG19 demonstrates strong learning performance. The ReLU activation function employed after each convolutional layer enables the model to effectively capture complex and nonlinear relationships. Furthermore, successive max-pooling layers progressively reduce the spatial resolution of the images, ensuring that the computational cost remains manageable [20].

2.4. SqueezeNet

SqueezeNet is a lightweight convolutional neural network developed for deep learning and computer vision. This model is designed to achieve low computational costs and high accuracy [21]. Unlike conventional deep convolutional neural network architectures, SqueezeNet adopts an approach that maintains high classification performance while employing a significantly smaller model structure. Consequently, it provides an effective solution for applications operating under limited computational and memory resources, such as

embedded systems and mobile platforms [22]. SqueezeNet is a convolutional neural network architecture designed around Fire modules, which consist of two sequential stages: Squeeze and Expand. In the Squeeze stage, input feature maps are compressed using 1×1 convolutions, resulting in a substantial reduction in the number of parameters. Subsequently, the Expand stage employs a combination of 1×1 and 3×3 convolutions to enlarge the feature representation. This architectural strategy enhances computational efficiency while maintaining the model's learning performance [21]. This architectural structure reduces the number of parameters and also optimizes memory usage, enabling the model to provide high performance in a compact structure [23].

2.5. Confusion Matrix

The confusion matrix is a fundamental analytical tool used to evaluate the performance of classification-based machine learning models. By presenting correct and incorrect predictions across distinct categories, it enables a systematic analysis of both classification accuracy and error types. Although it is most commonly applied in binary classification scenarios, the confusion matrix can also be effectively extended to multi-class problems. It consists of four core components: true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). These components facilitate a clear assessment of the model's predictive accuracy and error characteristics [24]. The confusion matrix plays a role in calculating metrics such as the model's sensitivity, specificity, positive predictive value (precision), and F1 score. Interpreting the confusion matrix is important to understand which areas the model is successful in and which types of errors it makes. For example, high true positive (TP) and true negative (TN) values indicate that the model is generally successful in the classification task. However, analysis of false positive (FP) and false negative (FN) values shows which classes the model is prone to making errors in and can help understand the possible causes of these errors [25]. An example confusion matrix is given in Figure 1.

	PREDICTED		
	Clean	Dirty	
ACTUAL	Clean	TP	FN
	Dirty	FP	TN

Figure 1. Confusion matrix example

2.6. Performance Metrics

Various performance metrics are employed to evaluate the effectiveness of machine learning-based classification models. Among the most commonly used metrics are accuracy, precision, recall, and the F1 score. These metrics examine different aspects of model behavior, enabling a comprehensive analysis of both overall performance and error characteristics. Accuracy represents the proportion of correctly predicted instances and is often used to provide an initial overview of model performance. However, particularly in datasets with imbalanced class distributions, accuracy alone is not a sufficient evaluation criterion, as no single metric can fully capture all types of classification errors [25]. Precision measures how many of the model's positive predictions are correct, and focuses specifically on minimizing the number of false positives (FP). Performance metrics and their formulas are given in Table 1.

Table 1. Performance Metrics and Their Formulas

Metrics	Equation
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN} \times 100$
Precision	$\frac{TP}{TP + FP}$
Recall	$\frac{TP}{TP + FN}$
F-1 Score	$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

III. RESULT AND DISCUSSION

In this study, it is aimed to detect dust on solar panels through images. Solar Photovoltaics Panel for Dust Detection dataset is used [26]. There are 502 images in the “clean” class and 340 images in the “dirty” class in the dataset. These images are classified with CNN architectures SqueezeNet, InceptionV3, VGG16 and VGG19. In addition, images are classified by combining the image features obtained from these architectures to obtain a more powerful model. The obtained results are compared. Coding is done in Python programming language. The flow diagram of the study is given in Figure 2

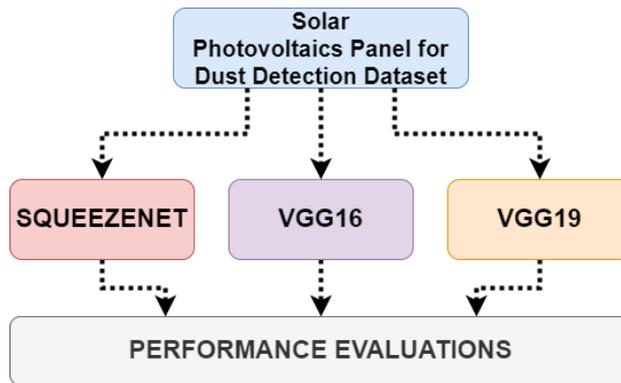


Figure 2. Flow chart of this study

As a result of the training and tests, confusion matrix performance metrics are obtained for each model. The confusion matrix obtained as a result of the training and tests of the SqueezeNet model is shown in Figure 3.

ACTUAL	PREDICTED	
	Clean	Dirty
Clean	492	10
Dirty	16	324

Figure 3. Confusion matrix of SqueezeNet model

According to Figure 3, the TP value is 492. The TN value is 324. The FN value is 10. The FP value is 16. 492 images of the “clean” class were correctly classified. 324 images of the “dirty” class were correctly classified. A total of 816 images were correctly classified. 10 images that actually belonged to the “clean” class were classified as “dirty”. 16 images that actually belonged to the “dirty” class were classified as “clean”. A total

of 26 images were incorrectly classified. Based on the data obtained from the confusion matrix, the performance of the SqueezeNet model was evaluated using accuracy, precision, recall, and F1 score metrics. The accuracy of the model was calculated as 96.9%, while the precision, recall, and F1 score values were all obtained as 0.969. In addition, the training and testing times of the model were measured as 21.656 seconds and 2.726 seconds, respectively. These results indicate that the SqueezeNet model is capable of classifying images with a high level of accuracy. Furthermore, the high precision, recall, and F1 score values are consistent with the obtained accuracy, further confirming the robustness of the model’s classification performance. The confusion matrix of the VGG16 model is presented in Figure 4.

	PREDICTED		
	Clean	Dirty	
ACTUAL	Clean	495	7
	Dirty	12	328

Figure 4. Confusion matrix of VGG16 model

According to Figure 4, the TP (True Positive) value is 495. The TN (True Negative) value is 328. The FN (False Negative) value is 7. The FP (False Positive) value is 12. 495 images belonging to the “clean” class were correctly classified. 328 images belonging to the “dirty” class were correctly classified. A total of 823 images were correctly classified, while 7 images belonging to the “clean” class were misclassified as “dirty,” and 12 images from the “dirty” class were incorrectly classified as “clean,” resulting in 19 misclassified samples in total. Based on the confusion matrix data, the performance of the VGG16 model was evaluated using accuracy, precision, recall, and F1 score metrics. The accuracy of the model was calculated as 98.0%, whereas the precision, recall, and F1 score values were obtained as 0.976, 0.986, and 0.981, respectively. In addition, the training and testing times of the model were measured as 21.656 seconds and 2.726 seconds, respectively. These results demonstrate that the VGG16 model achieves a high level of classification performance. In particular, the consistently high precision, recall, and F1 score values, together with the accuracy metric, indicate that the model exhibits a balanced and reliable classification behavior. The confusion matrix of the VGG19 model is presented in Figure 5.

	PREDICTED		
	Clean	Dirty	
ACTUAL	Clean	498	4
	Dirty	10	334

Figure 5. Confusion matrix of VGG19 model

According to Figure 5, the TP (True Positive) value is 498. The TN (True Negative) value is 334. The FN (False Negative) value is 4. The FP (False Positive) value is 10. 498 images belonging to the “clean” class were correctly classified. 334 images belonging to the “dirty” class were correctly classified. The VGG19 model correctly classified a total of 832 images. However, 4 images belonging to the “clean” class were incorrectly classified as “dirty,” while 10 images from the “dirty” class were misclassified as “clean,” resulting in 14 misclassified images in total. Based on the confusion matrix data, the fundamental performance metrics of the model, including accuracy, precision, recall, and F1 score, were computed. The results indicate that the VGG19 model achieved an accuracy of 98.3%, with precision, recall, and F1 score values of 0.980, 0.992, and 0.986, respectively. Furthermore, the training and testing times of the model were measured as 21.656 seconds and 2.726 seconds, respectively. An overall evaluation of these performance metrics demonstrates that the VGG19 model exhibits high accuracy and stable performance in the image classification task. In particular, the consistently high precision, recall, and F1 score values, in alignment with the accuracy metric, confirm that the model possesses strong discriminative capability and reliable overall performance. The performance metrics of all evaluated models are presented in Table 2.

Table 2. Performance Metrics of All Models

Model	Accuracy (%)	Precision	Recall	F1 Score
SqueezeNet	96.9	0.969	0.969	0.969
VGG16	97.9	0.976	0.986	0.981
VGG19	98.3	0.980	0.992	0.986

As seen in Table 2, the classification performances of three different deep learning models are quite high. The SqueezeNet model achieved a successful result with 96.9% accuracy rate; and the precision, recall and F1 Score values showed a balanced performance with 0.969. The VGG16 model took these results one step further and provided a more effective classification success with 97.9% accuracy, 0.976 precision, 0.986 recall and 0.981 F1 Score values. The best performance belongs to the VGG19 model; the model, which reached 98.3% accuracy rate, gave the most successful results in the classification task with 0.980 precision, 0.992 recall and 0.986 F1 Score. In the light of these metrics, it can be said that all three models provide high reliability in the field of image classification, but VGG19 stands out in terms of general accuracy and especially minimizing errors (FN and FP).

IV. CONCLUSION

In this study, the automatic detection of dust accumulation on solar panels was investigated using image processing and deep learning techniques. For this purpose, the Solar Photovoltaics Panel for Dust Detection dataset was utilized, and the images were classified using three different convolutional neural network architectures, namely SqueezeNet, VGG16, and VGG19. The dataset consists of 502 images belonging to the “clean” class and 340 images belonging to the “dirty” class. Performance comparisons revealed that the SqueezeNet model achieved an accuracy of 96.9%, with precision, recall, and F1 score values of 0.969, 0.969, and 0.969, respectively, indicating an adequate classification performance. The VGG16 model demonstrated improved performance, achieving 97.9% accuracy, along with precision, recall, and F1 score values of 0.976, 0.986, and 0.981, respectively. Among the evaluated models, VGG19 exhibited the highest classification performance, outperforming the other architectures with an accuracy of 98.3%, precision of 0.980, recall of 0.992, and an F1 score of 0.986. These findings demonstrate that image-based deep learning approaches provide an effective and reliable solution for maintenance and performance monitoring processes of solar panels.

However, there are some limitations to this study. The dataset used consists of a limited number of images taken in controlled environments and does not fully reflect the variable environmental factors in real field conditions. In addition, there is a significant imbalance between classes (clean > dirty), which may affect the learning process of some models.

As part of future studies, it is recommended that the model be integrated into a real-time surveillance system and tested with live images obtained with drones or fixed cameras. In addition, the generalization ability of the model can be increased by enriching the dataset with images taken in different lighting, weather conditions and angles in a wider scope. With the mobile or embedded systems to be developed, it is possible to run these models in real time in the field and integrate them into solar panel cleaning automations. However, advanced tasks such as multi-class classification of dust accumulation degrees (e.g. light, moderate, heavy pollution) and estimating their impact on the efficiency of panels can also be integrated into these systems.

REFERENCES

- [1]. R. Butuner *et al.*, “Classification of deep image features of lentil varieties with machine learning techniques,” *European Food Research and Technology*, vol. 249, no. 5, pp. 1303–1316, 2023.
- [2]. F. Chollet, “Xception: Deep learning with depthwise separable convolutions,” in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, pp. 1251–1258, 2017.
- [3]. I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.
- [4]. S. Han, H. Mao, and W. J. Dally, “Deep compression: Compressing deep neural networks with pruning, trained quantization and Huffman coding,” *arXiv preprint arXiv:1510.00149*, 2015.
- [5]. K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, pp. 770–778, 2016.
- [6]. A. G. Howard *et al.*, “MobileNets: Efficient convolutional neural networks for mobile vision applications,” *arXiv preprint arXiv:1704.04861*, 2017.
- [7]. F. N. Iandola *et al.*, “SqueezeNet: AlexNet-level accuracy with 50× fewer parameters and <0.5 MB model size,” *arXiv preprint arXiv:1602.07360*, 2016.
- [8]. J. K. Kaldellis, A. Kokala, and M. Kapsali, “Natural air pollution deposition impact on the efficiency of PV panels in urban environment,” *Fresenius Environmental Bulletin*, vol. 19, no. 12, pp. 2864–2872, 2010.
- [9]. A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” *Advances in Neural Information Processing Systems*, vol. 25, 2012.

- [10]. Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998.
- [11]. S. Y. Lermi and T. O. Onur, "Gunes paneli kusurlarının derin öğrenme tabanlı sınıflandırılması," *International Journal of Advances in Engineering and Pure Sciences*, vol. 36, no. 2, pp. 140–149, 2024.
- [12]. W. Liu *et al.*, "SSD: Single shot multibox detector," in *Computer Vision – ECCV 2016*. Springer, pp. 21–37, 2016.
- [13]. D. Matusz-Kalasz and I. Bodnar, "Operation problems of solar panel caused by the surface contamination," *Energies*, vol. 14, no. 17, Art. no. 5461, 2021.
- [14]. R. N. Myyas *et al.*, "A novel solar panel cleaning mechanism to improve performance and harvesting rainwater," *Solar Energy*, vol. 237, pp. 19–28, 2022.
- [15]. M. S. H. Onim *et al.*, "SolNet: A convolutional neural network for detecting dust on solar panels," *Energies*, vol. 16, no. 1, Art. no. 155, 2022.
- [16]. H. Park *et al.*, "Utilization of robotics for solar panel cleaning and maintenance," *Konya Journal of Engineering Sciences*, vol. 7, no. 4, pp. 768–775, 2019.
- [17]. D. M. Powers, "Evaluation: From precision, recall and F-measure to ROC, informedness, markedness and correlation," *arXiv preprint arXiv:2010.16061*, 2020.
- [18]. R. Selbas and H. Cetin, "Fotovoltaik güneş santrallerinin verimlerinin değişiminin incelenmesi," *Uluslararası Sürdürülebilir Mühendislik ve Teknoloji Dergisi*, vol. 6, no. 1, pp. 10–17, 2022.
- [19]. S. Shamsir, "Solar photovoltaics panel for dust detection," Kaggle Dataset. [Online]. Available: <https://www.kaggle.com/datasets/safwanshamsir99/solar-photovoltaics-panel-for-dust-detection>
- [20]. K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.
- [21]. M. Sokolova and G. Lapalme, "A systematic analysis of performance measures for classification tasks," *Information Processing & Management*, vol. 45, no. 4, pp. 427–437, 2009.
- [22]. C. Szegedy *et al.*, "Going deeper with convolutions," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, pp. 1–9, 2015.
- [23]. Y. S. Taspınar, "Light weight convolutional neural network and low-dimensional images transformation approach for classification of thermal images," *Case Studies in Thermal Engineering*, vol. 41, Art. no. 102670, 2023.
- [24]. Y. S. Taspınar and M. Selek, "Object recognition with hybrid deep learning methods and testing on embedded systems," *International Journal of Intelligent Systems and Applications in Engineering*, 2020.
- [25]. W. K. Yap, R. Galet, and K. C. Yeo, "Quantitative analysis of dust and soiling on solar PV panels in the tropics utilizing image-processing methods," in *Asia-Pacific Solar Research Conference*, 2015.
- [26]. Y. Zatsarinnaya, A. Logacheva, and D. Amirov, "Contamination of solar panels as factor in selecting location for construction and operation of solar power plants in Russia," in *2019 Int. Conf. on Industrial Engineering, Applications and Manufacturing (ICIEAM)*. IEEE, 2019.