International Journal of Computational and Experimental Science and ENgineering
(IJCESEN)
Vol. 11-No.1 (2025) pp. 873-878
http://www.ijcesen.com
ISSN: 2149-9144

Research Article

Dust Detection on Solar Photovoltaic Panels Used in Optoelectronics with Convolutional Neural Network-Based Deep Learning Models

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Article Info:

DOI: 10.22399/ijcesen.922
Received : 17 January 2025
Accepted : 11 February 2025

Keywords :

Optoelectronics,
Photovoltaic Panels,
Dust Detection,
Deep Learning,
Artificial Intelligence.

Abstract:

Solar photovoltaic panels, one of the optoelectronic device types, contain a large number of photovoltaic cells. The maintenance of these solar panels with photovoltaic cells is very important for the efficiency of the energy obtained from the panel. As time passes, dust may form on the panels due to various weather conditions and environments where the panels are located. In order to maintain the panels in a timely manner and increase energy efficiency, this study aims to detect the dust on the panels. For this reason, an open source dataset consisting of normal, clean and well-maintained solar photovoltaic panels and solar photovoltaic panels containing dust was used. Since the amount of the dataset is small and the amounts in the classes are unbalanced, firstly, various data augmentation operations were performed to increase the number of data amounts and make it balanced. In order to use this balanced dataset in the classification phase with deep learning models, the dataset was divided into 80% training and 20% testing. After this process, a total of four deep learning models based on convolutional neural networks, including MobileNetv1 for dust detection in solar photovoltaic panels and ResNet models with three different number of layers, were used. During these processes, two different optimization methods were used to train each model. As a result of these detection studies, the highest accuracy value was found to be 0.993 in the ResNet model, which was trained using the AdamW optimization method and had 18 layers.

1. Introduction

One of the most important devices used in optoelectronics is solar photovoltaic panels. These panels contain a large number of photovoltaic cells. The working principle of photovoltaic cells, which are a p-n junction device consisting of p-type, which refers to positively charged holes, and n-type, which refers to negatively charged electrons, is based on the photovoltaic effect [1]. Thanks to this photovoltaic effect, sunlight can be converted into electrical energy. When we consider the working details of the photovoltaic cell, first of all, the sunlight consisting of photons hits the cell surface and penetrates the semiconductor material on the surface. After the sunlight is absorbed with this process, this energy from the photons in the sunlight allows the electrons in the semiconductor material to break free from their atomic bonds, resulting in the formation of electron-hole pairs, which are free-moving negatively charged electrons and positively charged holes. Electrons are pushed towards the n-type side of the cell and holes are pushed towards the p-type side. These separated electrons create an electric current on the cell surface. Thus, when an external electrical load is connected to the photovoltaic cell, electric power is generated and/or various devices can be powered by the electron flow [2]. Analyzing the equivalent circuit models of photovoltaic cells; there are different models as ideal model, single diode and two diode. While the ideal model equivalent circuit does not include any series resistance and shunt resistance, the equivalent circuit of both single diode and two diode models include series and shunt resistors in addition to the difference in the number of diodes [3]. Figure 1 shows a model of an equivalent circuit of a photovoltaic cell with two diodes. Examining the Figure 1 given above; it is observed that the circuit elements of the photovoltaic cell equivalent circuit consist of a current source, two diodes and two resistors. Thus, I_{ph} represents the current generated by the

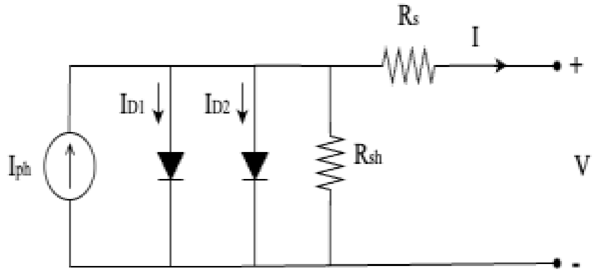

Figure 1. *Two diode equivalent circuit model of a photovoltaic cell*

photovoltaic cell due to sunlight, diodes represent the pn junction behavior of the cell, I_{D1} and I_{D2} represent the currents flowing through these diodes, R_s represents the series resistance indicating the internal resistance of the cell, and R_{sh} represents the shunt resistance affecting the overall current-voltage characteristics of the cell [4]. The mathematical expression for this circuit model of the photovoltaic cell is given in equation 1 below.

$$I_{pv} = I_{ph} - I_{D1} - I_{D2} - \frac{V_D}{R_{sh}} \qquad (1)$$

Considering equation 1 above, it is observed that in order to calculate the I_{pv} current for a photovoltaic cell, the I_{D1} and I_{D2} currents must be subtracted from the I_{ph} photocurrent and also subtracted from the ratio of the V_D voltage to the R_{sh} resistance [4].
Photovoltaic cell types are very diverse when investigated. These types include organic photovoltaic cells, multijunction solar cells, thin-film solar cells, polycrystalline silicon solar cells, monocrystalline silicon solar cells, dye-sensitized solar cells, perovskite solar cells, tandem solar cells and silicon photovoltaic cells [2]. In addition to these, Highly Efficient Solar Cell Architectures include passive emitter and rear locally diffused (PERL) solar cell, heterojunction with intrinsic thin-layer (HIT) solar cell, passive emitter and rear cells (PERC) solar cell and tunnel oxide passivated contact (TOPCon) solar cell [5]. Solar photovoltaic panels require regular maintenance for energy efficiency. However, due to their environment and weather conditions, dust may form on the panels. In order to increase energy efficiency and to support timely maintenance, this study uses deep learning to perform dust detection on solar photovoltaic panels. In this context, the main contributions of the study to the literature, its differences from the literature and its originality points are listed below.

- Since the quantities in the classes of the dataset used for solar photovoltaic panels were unbalanced, data augmentation operations were performed to balance the dataset.
- In binary classification on panel images for dust detection, four deep learning models were used, rather than relying on a single deep learning model.
- In the models used for classification, current deep learning models based on convolutional neural networks, which are frequently used in recent years, were preferred instead of machine learning.
- Instead of using a single optimization method in the training of deep learning models, two different optimization methods are used.
- In order to increase the reliability of dust detection results and to analyze the results accurately, important metrics such as accuracy, precision and recall were obtained in terms of evalution metrics.

2. Related Works

In the literature, there are a wide variety of dust detection studies on solar photovoltaic panels using deep learning. Onim et al. performed classification processes with deep learning models such as AlexNet, VGG and their own proposed deep learning model to detect dust on the solar panel database they created, and the highest accuracy value was obtained as 98.2% in the proposed deep learning model called SolNet [6]. Cruz-Rojas et al. performed various data preprocessing operations on three different dusty solar panel datasets and performed segmentation operations for dust detection in panels using machine learning models such as XGBoost, random forest and U-net deep learning model and the highest mean IoU value was found to be 89.38% [7]. Using 210 photovoltaic panels, Cui et al. obtained the highest mAP (mean average precision) value of 0.941 for segmentation with deep learning based Mask R-CNN on a dataset containing both real dust and simulated dust [8]. The highest accuracy value obtained by Prova using InceptionV3 deep learning on the test dataset related to 55% clean and 45% dusty solar panel dataset is 93.10% [9]. Oulefki et al. performed various segmentation processes to detect dust on solar panels using DeepSolarEye dataset and obtained a dice coefficient of 92% with the proposed model [10]. Mamdouh and Zaghloul used deep learning based Long Short-Term Memory networks (LSTMs) and Support Vector Regression (SVR) with Artificial Neural Networks (ANNs) for dust detection on two different solar panel datasets and the highest accuracy value was 99.50% [11].
The highest accuracy value obtained by Bassil et al. is 89.8% by classifying a total of five different deep learning based models such as VGG, MobileNet using dusty and clean solar panel datasets shared

open-source from Kaggle platform [12]. Mohammed and Alawi obtained an accuracy of 98.69% as a result of the detection process performed with the proposed deep learning model based on EfficientNet using two different solar panel datasets [13]. The highest accuracy value obtained by He et al. using a MobileNet-based model proposed for dust detection after some data preprocessing operations on a solar panel dataset shared open-source from Kaggle platform is 94% [14]. Shah et. al. obtained 92.34% accuracy with InceptionV3 deep learning model for dust detection on solar panels [15]. The mAP value obtained by Xie et. al. with YOLOv8 deep learning based model for artificial dust detection with real samples on open source photovoltaic panel database is 0.948 [16]. Alatwi et al. used different versions of deep learning models such as EfficientNet, DenseNet, VGG with different number of layers in dust detection processes performed on solar panels in order to increase both low cost and energy efficiency, and as a result of classification processes, the highest accuracy value as 86.79% was found in the DenseNet model with 169 layers [17]. Sefer and Kaya performed dust detection on solar panels with 10 different deep learning models and the proposed ensemble model and obtained a classification accuracy of 99.31% [18]. In ResNet, VGG and MobileNet models, Shao et al. performed dust detection on solar panels using the improved Adam optimization algorithm and the highest accuracy was found in the MobileNet model with 99.43% [19]. Comparisons of some important studies in the literature on solar panels in recent years with deep learning are given in Table 1. When table 1 is examined, it is observed that there are classification, segmentation or object detection

Table 1. *Some significant studies on dust detection.*

Reference	Types	Model	Results
[6]	Classification	SolNet	98.2% Accuracy
[8]	Segmentation	Mask R-CNN	0.941 mAP
[9]	Classification	InceptionV3	93.10% Accuracy
[10]	Segmentation	Custom Model	92% Dice
[13]	Classification	EfficientNet	98.69% Accuracy
[14]	Classification	Mobile Net	94% Accuracy
[16]	Object Detection	YOLOv8	0.941 mAP
[17]	Classification	Dense Net169	86.79% Accuracy
[18]	Classification	Ensemble Model	99.31% Accuracy

type studies on dust detection in the literature and deep learning based mdoels are used. In this study, four deep learning models were used for dust detection of solar photovoltaic panels used in the field of optoelectronics.

3. Material and Methods

In the study, a dataset containing solar photovoltaic panels and shared open-source on the Kaggle platform was used [20]. This dataset is also based on the solar panel dataset shared by Onim et al. in 2022 [6]. The dataset classes consist of two classes: clean, normal and well-maintained solar photovoltaic panels and dusty panels. When the amount of dataset is analyzed, it is observed that there is an imbalance between the classes. For this reason, data augmentation was performed by randomly rotating the panel images at a certain angle and in different directions in order to stabilize the dataset and to better train the deep learning models. Thus, the amount of panels in the normal, clean class was approximately doubled, while the amount of panels containing dust was approximately tripled. After this process, the dataset was divided into 80% training and 20% validation. Information on the amount and distribution of the dataset is also given in Figure 2.

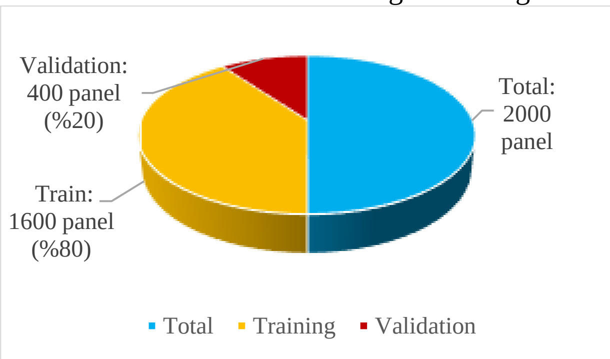

Figure 2. *Quantity and distribution of solar photovoltaic panel datasets*

Considering the figure 2, it is observed that there are 1600 training datasets and 400 validation datasets, totaling 2000 solar photovoltaic panel datasets. When the dataset is analyzed in terms of each class, there are 800 training and 200 validation data in each of the normal and dusty panel classes. Therefore, since the dataset is balanced, the total amount of both normal and dusty panels is 1000 each, and the total dataset is 2000. In addition, the amount of data augmented by these data augmentation steps used in deep learning models has more than doubled compared to the initial amount of data. Samples of the dataset are given in figure 3. When figure 3 is examined, it is observed that there

(a) Normal

(b) Dusty

Figure 3. *Normal and dusty samples of solar photovoltaic panel*

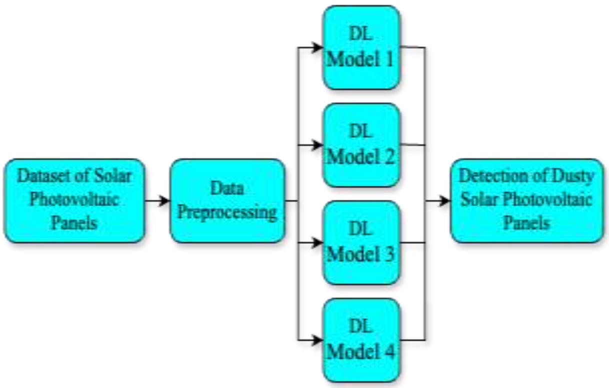

Figure 4. *Flowchart of dust detection on solar photocoltaic panels*

are three panel samples for the normal class and dusty class of the solar photovoltaic panel dataset.

In this study, four deep learning based models are used for dust detection in solar photovoltaic panels. These models are MobileNetV1, ResNet18, ResNet50 and ResNet152. Figure 4 shows in detail the flowchart applied for dust detection within the scope of the study. Examining the figure 4, it is observed that a data preprocessing process including data augmentation steps was first performed on the solar photovoltaic panel dataset. After this process, four deep learning (DL) models were used to perform dust detection on solar photovoltaic panels. The model corresponding to DL Model 1 in Figure 4 is the MobileNetV1 model, while the models corresponding to DL Model 2, DL Model 3 and DL Model 4 are ResNet-based deep learning models with 18 layers, 50 layers and 152 layers, respectively. All of these four models were chosen among the models related to the image classification task in the Hugging Face platform [21]. The content and details of these models are explained one by one in two subheadings.

3.1 MobileNetV1

The MobileNet deep learning model was presented in the literature by Howard et al. in 2017 and can be used in different problem solutions such as image classification and object detection. This model is based on convolutional neural networks and includes depthwise separable filters. In addition, pointwise convolution and depthwise convolution are also used in this MobileNet model [22]. In this study, MobileNetV1 is used and Google's model shared on the Hugging Face platform is preferred for the model version.

3.2 ResNet

The deep learning-based ResNet model was first introduced in the literature by He et al. in 2016 and is a model that includes building blocks related to residual learning. When we examine the block structures, it is observed that there are 3x3 convolution layers [23]. Three different versions of the ResNet model used in the study, 18-layer, 50-layer and 152-layer, were used, and the deep learning model shared by Microsoft on the Hugging Face platform was preferred.

4. Results

In order to detect solar photovoltaic panels containing dust, all important evaluation metrics were obtained as a result of the binary classification processes performed in this study. These metrics are precision (P.), recall (R.), f1, accuracy (Acc.) and the area under the receiver-operating characteristic curve (AUC) scores. In the study using MobileNetV1 based on convolutional neural networks and ResNet deep learning models with different layers, two different optimizers, AdamW [24] and stochastic gradient descent (SGD) [25], were used to train the models for deeper analysis of the results. The results with the models using AdamW and SGD optimizers are given in table 2. When table 2 is examined in detail; in the classification studies performed with four deep learning models, the highest accuracy value of 0.993 was found in DL Model 2, which corresponds to the ResNet18 model, where AdamW optimizer was used in model training. DL Model 1 corresponds to MobileNetV1 and DL Models 3 and 4 correspond to ResNet50 and ResNet152 respectively. Considering the classification results in terms of precision, it is observed that the highest score is obtained in MobileNetV1, while in terms of recall, the highest score is obtained in the ResNet18 model, as in the accuracy scores. Figure 5 shows the comparison of the classification results.

Table 2. *Results of dusty solar photovoltaic detection with DL models using AdamW and SGD optimizer*

Models	Acc.	P.	R.	AUC	F1
DL Model 1 (AdamW)	0.968	1.0	0.935	0.998	0.966
DL Model 1 (SGD)	0.56	0.554	0.615	0.634	0.583
DL Model 2 (AdamW)	0.993	0.985	1.0	0.999	0.993
DL Model 2 (SGD)	0.435	0.465	0.86	0.986	0.301
DL Model 3 (AdamW)	0.83	0.756	0.975	0.931	0.852
DL Model 3 (SGD)	0.465	0.476	0.69	0.399	0.563
DL Model 4 (AdamW)	0.913	0.884	0.95	0.972	0.916
DL Model 4 (SGD)	0.488	0.494	0.97	0.487	0.654

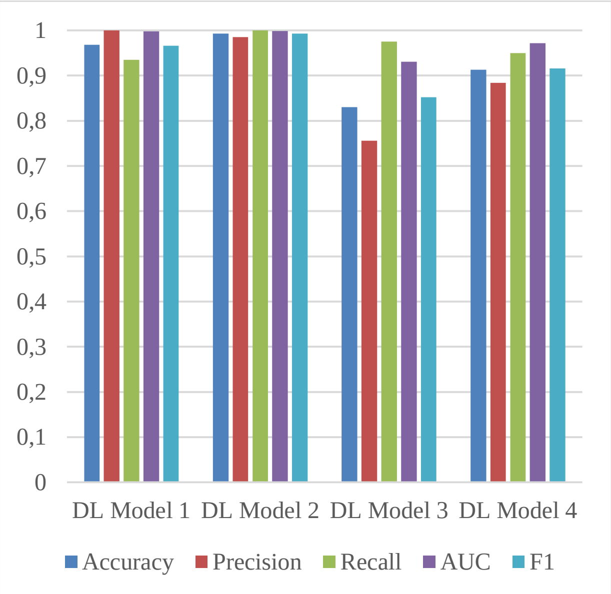

Figure 5. *Comparison of accuracy, f1-score, precision, recall and AUC results*

Figure 5 shows that the highest scores in accuracy, recall, AUC and f1 score metrics are obtained in the ResNet18 model. The metric results in this graph are the versions of the four deep learning models without the AdamW optimizer. When the classification results with ResNet models with different number of layers are analyzed in more depth, it is observed that the accuracy value decreases when the number of layers is increased from 18 to 50, while it increases when the number of layers is increased from 50 to 152. However, when the results of ResNet models with 18 and 152 layers are compared, it is observed that ResNet18 is more successful in detecting dust on solar photovoltaic panels. Similar work also reported in literature [26].

5. Conclusions and Future Works

In this study, dust detection processes in solar photovoltaic panels were performed. Two different optimizers and four deep learning models were used for detection and 8 different cases of deep learning models were used.
Among the detection studies performed with four models in total, three deep learning models based on ResNet with different layers and MobileNetV1 model, the highest classification result was achieved in the 18-layer ResNet model using the AdamW optimizer in the training phase. Using an open source dataset, data augmentation operations were performed to balance the dataset and the classes were harmonized in terms of the amount of dataset. Within the scope of this study, in which the effect of two different optimizers on the training of the deep learning model was examined, it was aimed to increase both energy efficiency and timely maintenance of the panels by performing dust detection operations on solar photovoltaic panels. In the future studies, different datasets can be used for dust detection in panels, additional data preprocessing and/or data augmentation operations can be performed, and an artificial intelligence system that can work in real time can be developed.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** Data used in this study are available at https://www.kaggle.com/datasets/gauravduttakiit/solar-panel-dust-detection (accessed on 5 December 2024).

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