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DETECTION OF DUST ON SOLAR PANELS WITH DEEP LEARNING

GÜNEŞ PANELLERİ ÜZERİNDEKİ TOZUN DERİN ÖĞRENME İLE TESPİTİ

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ABSTRACT

Solar energy is an environmentally friendly, clean, and sustainable alternative. The widespread use of this energy source offers excellent environmental and economic benefits. However, some factors affect the efficiency of solar panels. One of these factors is dust. When dust accumulates on the surface of solar panels, it can significantly reduce the efficiency of energy production. Therefore, detecting and quickly removing dust from solar panels is crucial. Managing this process with unmanned artificial intelligence systems, especially in large areas, will provide significant advantages in terms of time and cost. In recent years, convolutional neural networks have achieved significant success in image classification. In particular, transfer learning methods have proven their success in this field. In this study, we aim to solve a new task with limited data using pre-trained deep learning models (EfficientNetB3, ResNet50, MobileNet, VGG19, Xception, InceptionResNetV2, VGG16, ResNet101, DenseNet201, EfficientNetB7) to classify dirty and clean solar panels. These models were chosen because they each have different strengths and have performed well on various tasks. The models with the best performance among these models are combined to improve classification prediction. The proposed ensemble learning approach achieved 99.31% classification accuracy by considering the prediction results of the models with a voting approach. As a result, this approach aims to optimize the maintenance processes of solar energy systems, improve energy efficiency, and support sustainable energy use in the long term.

Keywords: Deep learning, energy efficiency, sustainable energy, transfer learning, ensemble learning

ÖZET

Güneş enerjisi, temiz ve sürdürülebilir bir enerji kaynağı olarak çevre dostu bir alternatiftir. Bu enerji kaynağının yaygınlaşması, hem çevre hem de ekonomik açıdan büyük faydalar sunar. Ancak, güneş panellerinin verimliliğini etkileyen bazı unsurlar vardır. Bu unsurlardan biri de tozdur. Toz, güneş panellerinin yüzeyine biriktiğinde enerji üretim verimliliğini önemli ölçüde düşürebilir. Bu nedenle, güneş panellerindeki tozun tespiti ve hızlı bir şekilde temizlenmesi büyük önem taşır. Özellikle geniş alanlarda bu sürecin insansız yapay zekâ sistemleriyle yönetilmesi, hem zaman hem de maliyet açısından önemli avantajlar sağlayacaktır. Son yıllarda evrişimsel sinir ağları görüntü sınıflandırma konusunda önemli başarılar elde etmiştir. Özellikle transfer öğrenme yöntemleri bu alanda başarısını kanıtlamıştır. Bu çalışmada, kirli ve temiz güneş panellerini sınıflandırmak için önceden eğitilmiş derin öğrenme modellerini (EfficientNetB3, ResNet50, MobileNet, VGG19, Xception, InceptionResNetV2, VGG16, ResNet101, DenseNet201, EfficientNetB7) kullanarak sınırlı veri ile yeni bir görevi çözme amaçlanmaktadır. Bu modellerin seçilme nedeni, her birinin farklı güçlü yönlere sahip olması ve çeşitli görevlerde başarılı performans sergilemiş olmalarıdır. Bu modeller arasında en iyi performansa sahip modeller, sınıflandırma tahminini iyileştirmek için birleştirilmiştir. Önerilen topluluk öğrenme yaklaşımı, modellerin tahmin sonuçlarını oylama yaklaşımıyla ele alarak %99,31 sınıflandırma doğruluğuna ulaşmıştır. Sonuç olarak, bu yaklaşım güneş enerjisi sistemlerinin bakım süreçlerini optimize etmeyi, enerji verimliliğini artırmayı ve uzun vadede sürdürülebilir enerji kullanımını desteklemeyi amaçlamaktadır.

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Anahtar Kelimeler: Derin öğrenme, enerji verimliliği, sürdürülebilir enerji, transfer öğrenme, topluluk öğrenme

INTRODUCTION

Solar energy emerges as an environmentally friendly, sustainable, and economical energy source. Both in Turkey and worldwide, solar energy utilization is steadily increasing. Solar energy contributes significantly to clean energy production and energy security. Countries can reduce their dependence on external energy sources by investing in solar energy, consequently diminishing reliance on fossil fuels. Despite its importance, various factors can affect the efficiency of solar panels, with dust accumulation on panel surfaces being a prominent concern (Çetin et al., 2019).

Dust accumulation can reduce sunlight absorption, consequently lowering energy production. Hence, regular detection and cleaning procedures regarding solar panel dust are crucial to ensure maximum system efficiency. Dust detection on solar panels can be performed through automatic systems or observers. These detections are vital for ensuring regular maintenance of panels, minimizing energy loss, and facilitating long-term sustainable energy production. Thus, emphasizing the general advantages of solar energy and the importance of dust detection and cleaning measures for panels constitutes a comprehensive energy strategy.

In recent years, deep learning-based approaches have successfully classified image data (Kaya et al., 2022; Utku et al., 2024). These methods are used in medical diagnostics, autonomous vehicles, various tasks, and almost every field today to classify objects and categories automatically. (Şenol et al., 2021). Deep learning approaches, which offer successful solutions in many vital areas, offer the potential to accelerate dust detection processes on solar panels, thereby enhancing energy efficiency. Deep learning models, which achieve more effective and accurate results than traditional methods, can effectively determine the degree of panel dusting and assist in optimizing maintenance processes. Consequently, using artificial intelligence systems, solar energy systems can operate more sustainably, durable, and efficiently.

There is considerable research in the literature to detect dirt on solar panels and thus improve efficiency. Davaadorj, et al.'s study, focuses on distinguishing various types of contaminants on solar panels. They utilized a Convolutional Neural Network (CNN) for this classification task, employing the Solar Panel Dust dataset generated by Deep Solar Eye, a pre-trained dataset. This dataset comprises a total of 45,649 images of solar panels and defines six distinct contamination categories, which are thoroughly analyzed. The dataset is divided into 70% for training, 20% for validation, and 10% for testing. The model used in this study is a nine-layer CNN. Although the training was initially set for 50 epochs, it was halted at the 19th epoch due to early stopping. The test results demonstrated a classification accuracy of 98%, highlighting the model's capability to identify different types of contaminants accurately. This success rate indicates the model's efficiency in recognizing various contaminant types on solar panels. The proposed method offers an effective solution for automatically identifying contaminants on solar panels (Davaadorj et al., 2021).

In the study conducted by Dwivedi and colleagues, reference is made to a dataset named "Solar Panel Soiling Image Dataset" for identifying defects in solar panels. This dataset, prepared by Deep Solar Eye, comprises 45,469 images. The images were captured every 5 seconds by an RGB camera, with a resolution set to 192×192 pixels. The dataset includes images captured under various artificial conditions representing potential soiling scenarios on solar panels. Additionally, various defect types representing soiling conditions were downloaded from Google. These defect types include bird droppings or nests, snow covering, cracks, shadows from trees, plants, or buildings, and hardened cement. The images were then resized to a resolution of 72×72 pixels and used for advanced image processing. In total, 4110 images were labeled according to the type of defect. The study utilized five different models, including MobileNet, VGG16, Xception, EfficientNetB7, and ResNet50, as well as the proposed VIT architecture. After 100 epochs, MobileNet achieved an accuracy of 88%, VGG16 92%, Xception 93%, EfficientNetB7 94%, ResNet50 96%, and the VIT architecture demonstrated the highest performance with an accuracy rate of 98.7%. The proposed VIT architecture in this study provides an effective solution for identifying defects in solar panels, achieving the highest accuracy rate (Dwivedi et al., 2024).

Ferrell and Anderson examine the fundamental stages of a machine learning project to determine the cleanliness status of solar panels. The study begins with data inspection and cleaning, aiming to develop a classifier to differentiate between clean and dusty panels. In this phase, inconsistencies and abnormal data points in the datasets are identified to contribute to developing a robust classifier. In the feature engineering stage, various preprocessing steps are applied to images to distinguish between clean and dusty panels and eliminate misleading images. Different convolutional neural network (CNN) configurations are explored during the model training process, and the training accuracy, test accuracy, and overfitting conditions are evaluated to select the most suitable model. The MobileNet model is highlighted for its high accuracy and low computational complexity. Additionally, the performance of pre-trained models on the extensive ImageNet dataset is examined. Comparisons among MobileNet, VGG 16, VGG19, InceptionNet, and Xception architectures demonstrate the impressive overall performance of MobileNet, particularly suitable for real-time applications. Finally, an in-depth analysis of the MobileNetV2 model in the study indicates that it does not meet the performance of the initial MobileNet model. Consequently, it is concluded that the MobileNet model is the most suitable for real-time applications and predictions, achieving a 79% accuracy rate (Ferrell & Anderson, 2023).

In Maity and colleagues' study, the adverse impact of dust accumulation on the electricity generation performance of solar panels is emphasized. The amount and size of dust accumulation obstruct the sunlight reaching the surface of solar panels, leading to power loss. As a solution to this issue, a Convolutional Neural Network (CNN)-based approach for dust detection is proposed. The suggested method involves the LeNet model trained on a labeled dataset consisting of images of dusty solar panels. This dataset, obtained from experimental setups, includes 30,000 solar panel images and voltage and current measurements to determine the effect of dust on panel performance as a power loss percentage. Additionally, data augmentation techniques are applied to this dataset. The dataset containing various types of dust, such as red soil, sand, white cement, and calcium carbonate, is used to understand and detect dust accumulation effects. The proposed CNN model is designed as a deep learning technique inspired by the visual cortex, capable of effectively operating on image data. The model obtained during the training process aims to identify dusty areas and determine the performance loss in solar panels. In their study, the proposed LeNet architecture achieved an accuracy rate of 80% (Maity et al., 2020).

In the study conducted by Onim and colleagues, the performance of SolNet, a specially developed CNN model for detecting dust accumulation on solar panels, is examined. The study introduces a dataset containing images of Bangladesh solar panels with different levels of dust. After collecting 2231 images, the data were sorted to classify 1130 images as clean and 1101 as dirty. Subsequently, all randomly shaped original images were resized to 227 × 227 × 3 dimensions. The SolNet model was tested in experiments compared to SOTA (State-of-the-Art) models. The proposed model achieved high success with 98.2% accuracy and 1.12 loss after 30 epochs with 56 million parameters. Additionally, it was noted that the model outperformed others with its low parameter count and training time. In the future, it is recommended to enhance the universality of SolNet by training it with datasets obtained from various regions worldwide and working with an expanded dataset including various types of pollutants (Onim et al., 2023).

Prabhakaran and his team presented a Real-Time Multi-Variable Deep Learning Model (RMVDM) developed to detect and classify photovoltaic (PV) panel faults. The method's performance was evaluated using real-time PV images at the Science and Technology Institute. Three different datasets were used in the study: one containing 500, another containing 1000, and the third containing 2000 images. RMVDM aims to detect and localize faults such as hotspots, cracks, dust, and micro-cracks. This study uses the Region-Based Histogram Approach (RHA) algorithm for processing datasets. Preprocessed images are processed using the Gray Tone Quantization Algorithm (GSQA), followed by feature extraction. Extracted features are trained with a Multi-Variable Deep Learning model containing neural structures for different classes. During the testing phase, input images undergo various operations, and the extracted features are passed to the trained model. The output layer measures a series of Fault Class Supports (DCS) to determine the fault class in the image. Additionally, RMVDM uses the Higher-Order Texture Localization (HOTL) technique to localize the fault. The proposed RMVDM model achieves high accuracy rates for different image datasets: 87% for 500 images, 88% for 1000 images, and 97.6% for 2000 images. This results in effective outcomes with high accuracy and low time complexity (Prabhakaran et al., 2023).

Selvi and other researchers conducted a study on detecting pollution in solar panel modules using deep learning. In this study, data was collected from a 15 kW solar energy system on an institute campus over six months, and a total of 300 images were used; 200 were clean, and 100 were dirty. Data augmentation techniques were employed to increase the number of images, which were then cleaned and classified. The MobileNetV2 network was pre-trained and achieved a 97% success rate on the dataset. However, the proposed method struggled to detect small areas of pollution accumulation, and class imbalance affected the model's training, necessitating improvements. To enhance the model's generalization ability and achieve better results, the study suggests using more diverse data and carefully adjusting parameters during the training process (Selvi et al., 2023).

The study by Zyout and Oatawneh leveraged convolutional neural network (CNN) models to characterize the surface of photovoltaic (PV) panels and detect defects. The study utilized a solar panel image dataset from popular online sources such as Google, Bing, and Yahoo. This dataset comprises 599 images, with 326 representing various defects and 273 depicting normal and functional solar panels. The images were resized to dimensions of 227x227x3. The research emphasizes the importance of appropriate inspection approaches in solar panel production. It focuses on the possibility of panels being damaged or soiled due to challenging operating conditions, damage, and dirt. It highlights the potential of deep learning and CNNs for solar panel defect inspection and detection alongside electroluminescence (EL), thermal or infrared (IR), and RGB images. Pre-trained models, including AlexNet, VGG-16, VGG-19, Inception V3, XCeption, and ResNet-50, were explored in the study. The results indicate the promising performance of transfer learning applied to AlexNet, achieving a 93.3% accuracy rate in detecting various defects on the surface of solar panels, thus demonstrating the potential of this approach (Zyout and Oatawneh, 2020).

This study aims to classify dusty and clean solar panels using deep transfer learning methods. Its goal is to create a new model by combining pre-trained transfer learning models to determine the cleanliness status of solar panels. The obtained models aim to optimize maintenance processes and improve the energy efficiency of solar energy systems. Additionally, the study is expected to contribute to sustainable energy usage.

The following section summarizes the dataset used in the study, the ten deep transfer learning methods, and their general architecture. The proposed ensemble learning method and performance evaluation metrics are explained in the same chapter. The experimental results section provides the processes applied to the dataset, the accuracy and loss figures obtained in the study, and the real and predicted values to understand better the test success of the ten transfer learning methods used. Additionally, information about the proposed method is given, and confusion matrices, accuracy rates, and classification reports obtained through the proposed method are presented. Comparative accuracy rates for the ten transfer learning methods are provided in tabular form to compare them with the proposed method. Finally, in the last section of the study, a general evaluation is made, and some suggestions are provided based on the findings obtained in this study.

MATERIALS AND METHODS

The Dataset

The dataset used in this study was created by collecting images of dirty and clean solar panels in various locations in Bangladesh (Onim et al., 2023). The fact that this dataset has images taken in different locations will allow us to evaluate different amounts of dusty solar panels. The dataset has 722 clean and 718 dirty images, totaling 1440 solar panel images. The nine images of dusty and clean solar panels in the data set are given in Figure 1.

All images in the dataset used in this study have different dimensions. These images were resized to 224 x 224 x 3 and made suitable for the input data. Since the number of images of dusty and clean solar panels in the dataset is almost equal, no data balancing was performed. After resizing the images, the dataset was divided into three groups: 70% training, 20% test, and the remaining 10% validation data. The data set is divided into groups, as shown in Table 1.

Table 1. Splitting the Dataset into Training-Testing-Validation

Total number of images	Training	Test	Validation
1440	1008	144	288

Figure 1. Image and Label Values Belonging to the Dataset.

Hardware and Software Environment

This study was conducted in the Google Colab environment. Google Colab provides users with a cloud-based service offering free GPU (Graphics Processing Unit) resources. This platform enables the execution of Python-based projects and training deep learning models with free GPU capabilities (Kanani & Padole, 2019). The study was created using Python code written on Jupyter notebooks within Google Colab. The dataset used, and all labels were saved to Google Drive through code, and these resources were utilized. Additionally, deep learning models were created and trained using TensorFlow's Keras API in this study.

Deep Transfer Learning Architectures

Deep transfer learning is a machine learning technique that enables knowledge acquired in one task to be utilized in another task (LeCun et al., 2015). Typically, it involves reusing a model trained on large datasets for similar tasks with smaller datasets, thereby achieving better results with less data. Deep transfer learning is particularly effective in training neural network models. This strategy involves taking the feature extractor part of a pre-trained model and using it to train the model with less data for a new task (Pan & Yang, 2009).

In this study, after preprocessing the dataset, ten different deep transfer learning architectures, including EfficientNetB3, EfficientNetB7 (Tan & Le, 2019), ResNet50, ResNet101 (He et al., 2016), MobileNet (Howard et al., 2017), VGG16, VGG19 (Simonyan & Zisserman, 2014), Xception (Chollet, 2017), InceptionResNetV2 (Szegedy et al., 2017), DenseNet201 (Huang et al., 2017), and were trained and tested on the same training and test datasets over 20 epochs. Various performance metrics were used to evaluate the performance of these architectures, including classification reports showing accuracy, F1 score, precision, and recall values. Additionally, graphs illustrating the changes in accuracy and loss values over the 20 epochs were generated.

Furthermore, to visualize each model's prediction performance on the test dataset, 12 images were printed on the screen in a 4 x 3 matrix format, showing the predicted and actual label values. This comprehensive evaluation using different performance metrics gave a clearer understanding of which models performed better and which performed worse.

Ensemble Learning

Ensemble learning is a learning paradigm that creates a more robust and balanced model by combining a series of models (Saqlain et al., 2019). This method is used to surpass the performance of a single model and typically aims to achieve better generalization capabilities, categorized into various subtypes. Voting is an essential stage of the ensemble learning used in this study. Ensemble learning enables various models to work together to make more accurate predictions. This method combines predictions from different models using the voting principle, reaching the final result (Sewell, 2008). The dataset is first preprocessed using this approach and then divided into training, test, and validation sets. These steps allow the data to be used more efficiently and the models to make more accurate predictions.

This study's ten transfer learning models were trained on these preprocessed datasets. Transfer learning models are deep learning models usually pre-trained on large and diversified datasets. They have the advantage of being trained more quickly and effectively on new tasks. Once the training process was complete and the models reached a particular learning success, each model made predictions on the test dataset.

At this point, the predictions made by each model independently were recorded for evaluation using the Voting method. The Voting method aims to obtain more reliable and accurate results by combining various model predictions. This method is based on a majority decision of the predictions from different models. That is, when determining which class each data point belongs to, the majority of models recommend choosing whichever class. From the recorded model predictions, combinations of triples were created, and their label values were combined. Since each combination reflects the perspective of different models, this method helps minimize the errors a single model can make.

For each image in the test dataset, a new label value is assigned according to the majority label determined by the Voting method. This process means determining the most reliable result from the predictions from the various models. Finally, to measure the label prediction success of these combinations, the label values of each combination are compared with the actual label values of the test dataset. Thus, the prediction success is measured, and the results are analyzed.

The results obtained using various performance evaluation metrics are presented. Performance evaluation metrics are critical to understanding how well the models work and where improvements are needed. Figure 2 schematically shows the details of the method and process proposed in this study. The diagram visually summarizes how the method is implemented and what is done at each stage.

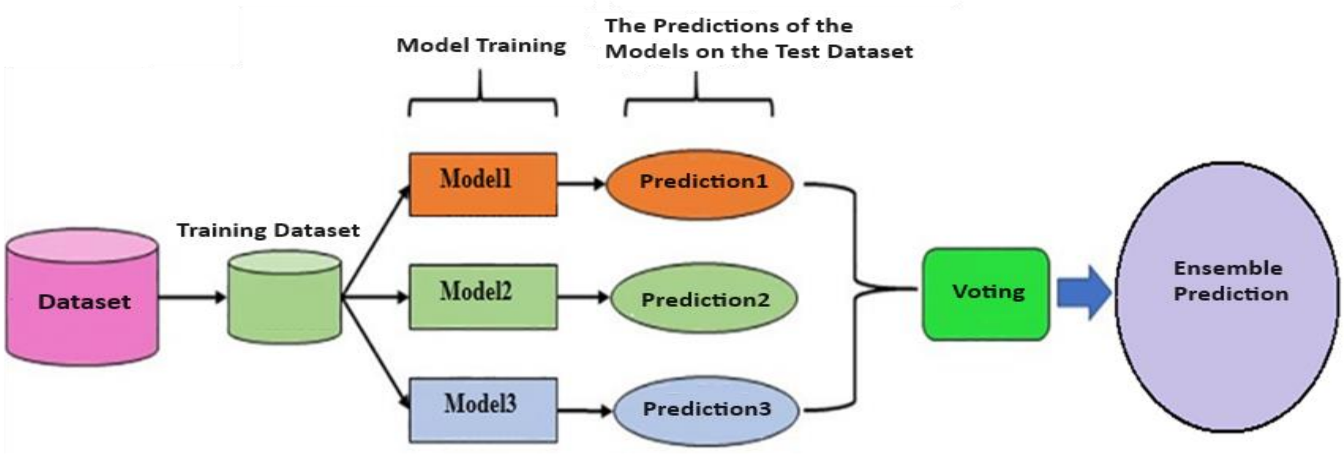


Figure 2. Schematic Description of the Proposed Method

Performance Evaluation

Evaluating the success and effectiveness of a study and understanding the performance of any model is a crucial step. These evaluations are conducted to determine the accuracy of applications, rectify errors, and provide guidance for future improvements. Utilizing performance evaluation metrics is essential to offer valuable insights to researchers and practitioners.

This study employs various performance evaluation metrics, including confusion matrix, precision, recall, F1 score, and accuracy. The confusion matrix is utilized to assess the performance of a classification model by illustrating the relationship between actual and predicted classes (Mete et al., 2020). Precision indicates the proportion of correctly predicted instances among those predicted to belong to a certain class. Recall, on the other hand, demonstrates the proportion of truly belonging instances to a specific class that was correctly predicted (Yarğı & Postalcıoğlu, 2021). The F1 score, which is the harmonic mean of precision and recall, is commonly used to evaluate a model's performance, especially in imbalanced datasets. Finally, accuracy represents the percentage of correctly classified instances among all predicted instances (Sokolova et al., 2006). These metrics collectively provide a comprehensive understanding of the performance of the models utilized in the study, aiding in comparisons and determining the degree of success of the applied method.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1\ Score = 2\ x\ \frac{TP + TN}{TP + FP + TN + FN} \tag{4}$$

EXPERIMENTAL STUDIES AND RESULTS

This study uses a dataset of solar panels from different regions of Bangladesh. The study aims to classify clean and dirty images in the dataset. The dataset consists of 1440 images in total. 70% of the dataset is allocated for training, 20% for testing, and 10% for validation. The images are of different sizes and resized to 224 x 224 x 3 for standardization. Ten pre-trained convolutional neural network (CNN) models (EfficientNetB3, ResNet50, MobileNet, VGG19, Xception, InceptionResNetV2, VGG16, ResNet101, DenseNet201, and EfficientNetB7) were used to classify the images.

Training and validation processes were carried out for each model in the training phase. The training process was successful, and performance evaluations were performed on the test dataset. The accuracy and loss value changes for each model were tracked for 20 epochs, and graphs were created. In the initialization phase, the images in the dataset were trained and tested separately with each transfer learning method. Accuracy and loss graphs for the ten trained models are given in Figure 3 and Figure 4. As can be seen from the training and test graphs in Figure 3 and Figure 4, the models gain better learning at each step. Among the models, InceptionResNetV2 has difficulty in learning. As a result of this learning, as can be seen in Table 2, InceptionResNetV2 achieved lower classification accuracy than the other models.

After the training phase was completed, the performance of each model on the test data was analyzed. Each model's accuracy, precision, recall, and F1 score performance results were analyzed and presented in Table 2 to evaluate the test results. According to Table 2, the ResNet101 model has the highest accuracy (97.92%) and F1 score (97.86%) value. EfficientNetB7 and DenseNet201 achieved the highest recall results (97.87%), while ResNet50 achieved the best precision value (99.26%).

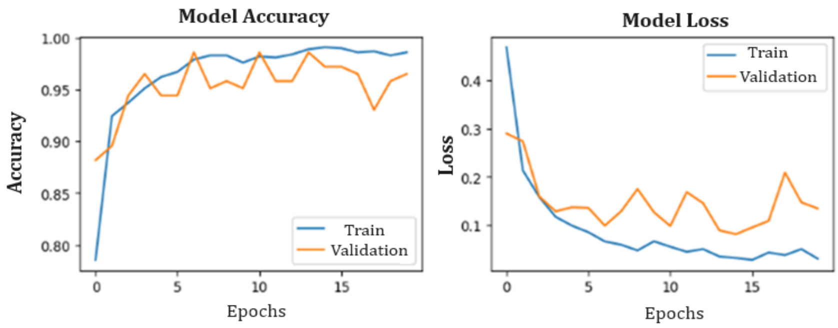
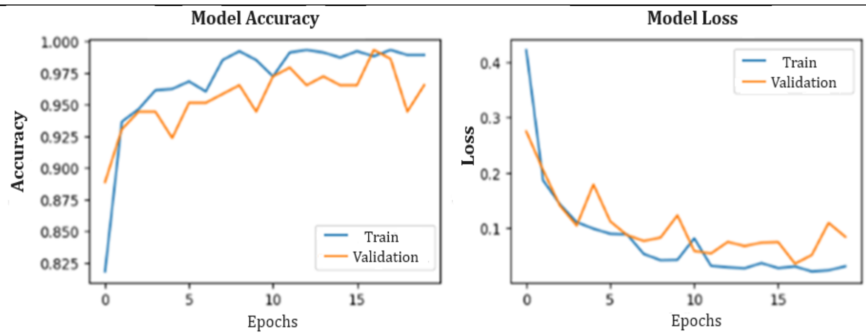
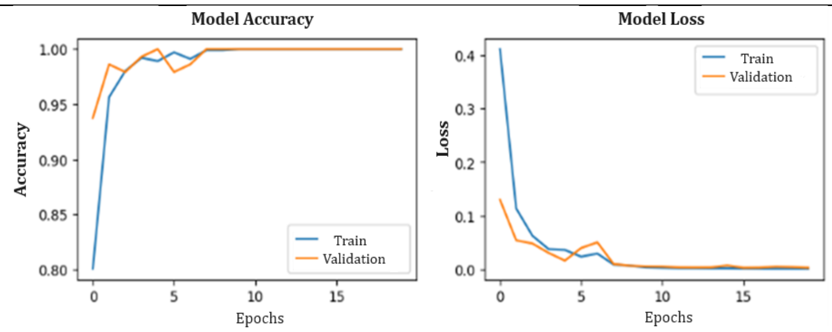
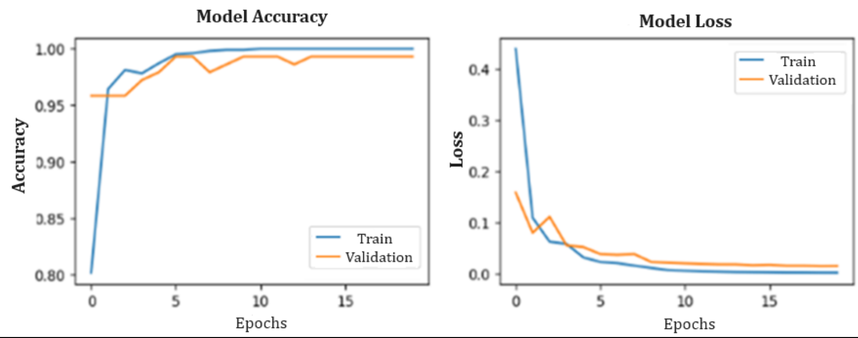
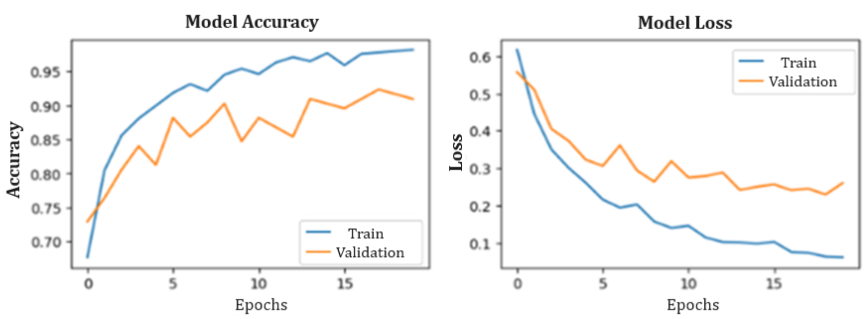
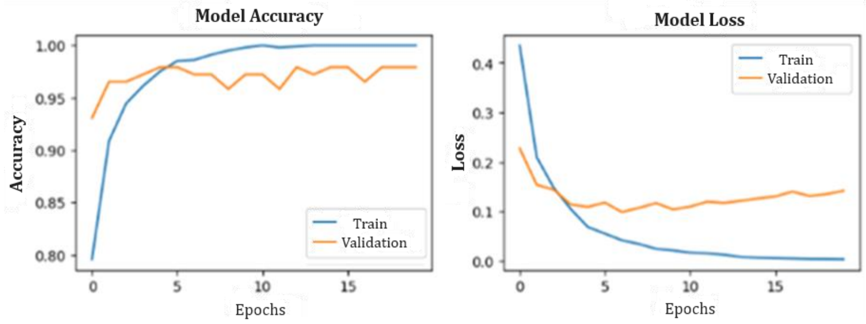
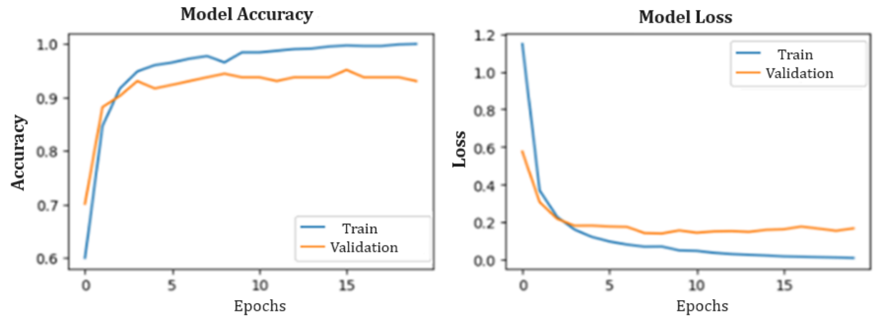
EfficientNetB3	
EfficientNetB7	
ResNet50	
ResNet101	
MobileNet	

Figure 3. Accuracy and Loss Graphs for EfficientNetB3, EfficientNetB7, ResNet50, ResNet101, and MobileNet

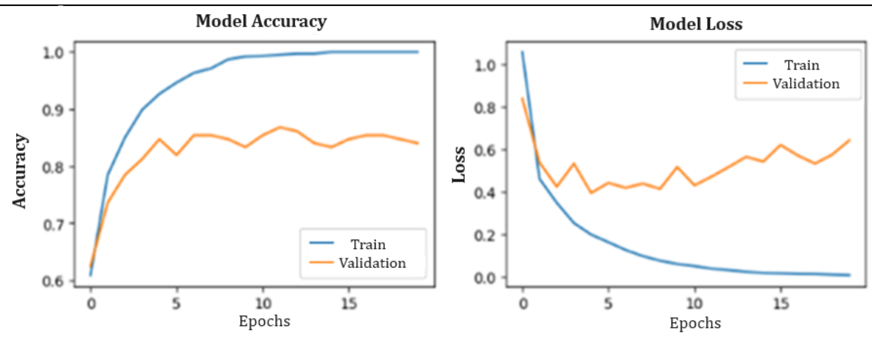
VGG16



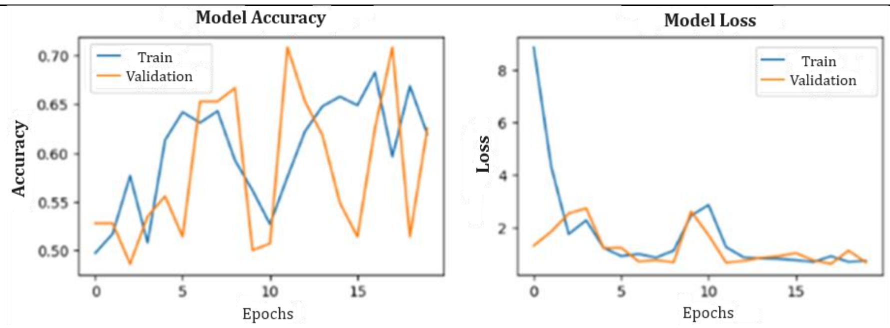
VGG19



Xception



InceptionResNetV2



DenseNet201

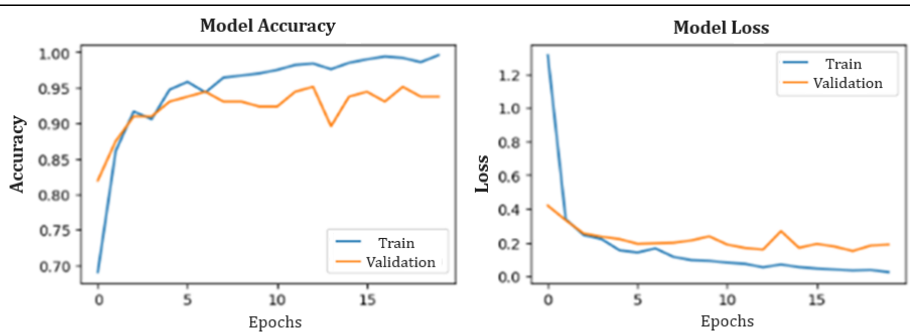


Figure 4. Accuracy and Loss Graphs for VGG16, VGG19, Xception, InceptionResNetV2, and DenseNet201

Table 2. Presents the Success Rates of Performance Evaluation Etrics for All Models (%)

Model	Accuracy	Precision	Recall	F1-Score
EfficientNetB3	96.53	97.12	95.74	96.43
EfficientNetB7	96.53	95.17	**97.87**	96.50
ResNet50	97.57	**99.26**	95.74	97.47
MobileNet	92.71	94.12	90.78	92.42
VGG19	94,10	96.97	90.78	93.77
Xception	85.76	86.76	83.69	85.20
InceptionResNetV2	65.97	60.49	87.94	71.68
VGG16	96.18	97.79	94.33	96.03
ResNet101	**97.92**	98.56	97.16	**97.86**
DenseNet201	96.18	94.52	**97.87**	96.17

Experimental Results of the Proposed Method

In the first phase of this study, ten different transfer learning models were trained on the same training dataset and tested on the same test dataset. To evaluate the success of the predictions Of each model on the test dataset, classification reports, accuracy and loss graphs on the training and validation datasets, and the final accuracy rate of each model are given. After analyzing the success rates of these models, the study aims to perform a prediction with an ensemble learning approach to increase this success. The proposed method uses a voting method by combining different transfer learning approaches. This approach records the predictions of ten models on the test dataset, and three combinations of these predictions are generated. The most frequently occurring label in these combinations was determined as the new prediction label value. The results were re-evaluated using these triple combinations on the entire test dataset.

The accuracy, precision, recall, and F1-Score results of the top five combinations with the best results are shown in Table 3 to evaluate the performance results of the proposed method. Proposed Method 1 (EfficientNetB3, VGG16, DenseNet201) and Proposed Method 2 (EfficientNetB3, ResNet101, DenseNet201) achieved the best accuracy, recall and F1-Score performance values. Proposed Method 3 (VGG16, ResNet101, ResNet50) and Proposed Method 4 (VGG16, ResNet101, EfficientNetB7) obtained the best precision values. EfficientNetB3, DenseNet201, ResNet101, and VGG16 methods individually achieved over 96% classification accuracy. With the triple voting technique, these methods achieved 99.31% classification accuracy. When we look at the results, we can see that the combination of the models that achieved the best results individually has resulted in a more successful result. The results also show the reliability of the voting method used.

Table 4 shows the studies in the literature on dust detection in solar panels and the classification accuracy results of the proposed method. As seen in Table 4, Dwivedi et al. obtained the highest classification accuracy for dust detection in solar panels in previous studies, 98.7%. This study obtained 99.31% classification accuracy with the ensemble learning approach, which evaluates the predictions of transfer learning approaches together. The proposed method achieves the best result, demonstrating its robustness in detecting dirt on solar panels.

Table 3. The Success Rates of Performance Evaluation Metrics for the Top 5 Combinations

Combinations	Accuracy	Precision	Recall	F1-Score
EfficientNetB3, VGG16, DenseNet201	**%99.31**	%99.29	**%99.29**	**%99.29**
EfficientNetB3, ResNet101, DenseNet201	**%99.31**	%99.29	**%99.29**	**%99.29**
VGG16, ResNet101, ResNet50	%98.96	**%100**	%97.87	%98.92
VGG16, ResNet101, EfficientNetB7	%98.96	**%100**	%97.87	%98.92
EfficientNetB3, VGG16, ResNet101	%98.61	%99.28	%97.87	%98.57

Table 4. Studies on Dust Detection in Solar Panels in the Literature

The Method	Year	Accuracy
AlexNet (Zyout ve Oatawneh., 2020)	2020	% 93.3
LeNet (Maity et al., 2020)	2020	% 80.0
CNN (Davaadorj et al., 2021)	2021	% 98.0
MobileNetV2 (Ferrell ve Anderson., 2023)	2023	% 79.0
SolNet (Onim et al., 2023)	2023	% 98.2
RMVDM (Prabhakaran, 2023)	2023	% 97.6
MobileNetV2 (Selvi et al., 2023)	2023	% 97.0
ViT (Dwivedi et al., 2024)	2024	% 98.7
The Proposed Method	2024	**%99.31**

DISCUSSION

Deep transfer learning architectures can achieve different results depending on the applied dataset. For this purpose, in the proposed work, experiments are conducted on various models and EfficientNetB3, ResNet50, MobileNet, VGG19, Xception, InceptionResNetV2, VGG16, ResNet101, DenseNet201, and EfficientNetB7 models are included for comparison. Many models were tested to determine the most appropriate model among these models, and only the results were included after sufficient results were obtained. The models used in this study are limited to the success of this dataset, and it is possible to obtain different results on other datasets.

While the deep learning models used achieved excellent results overall, the InceptionResNetV2 model achieved the lowest classification accuracy. Unlike the low accuracy result, the InceptionResNetV2 model achieved a better result in the Recall metric, which indicates the classification result for a single class. In addition, the Xception model also achieved relatively low success compared to other methods. ResNet101 deep learning architecture achieved the best classification accuracy and F1-Score result. The ResNet50 model achieved the best result in the Precision metric, while EfficientNetB7 achieved the best result in the Recall metric.

Ensemble learning is a powerful and efficient machine learning technique that combines predictions from multiple models to improve overall performance, accuracy, and robustness in classification tasks. By addressing the strengths and minimizing the weaknesses of individual models, ensemble methods often aim to achieve better results than a single model. One popular ensemble technique is voting, where multiple models are trained independently, and their predictions are aggregated to make a final decision. In classification tasks, this is realized as majority voting, where each model votes for a class label, and the class with the most votes is chosen as the final prediction. In this study, the voting technique combines the prediction results of three different models to improve classification performance. In future studies, the voting technique can be further improved by assigning weights to the models according to their accuracy and giving more influence to more reliable models. In this way, the voting technique can be improved by emphasizing the contributions of more robust models.

The dataset used in this study comprises images of clean and dirty solar panels collected from various locations in Bangladesh, introducing variability in dust levels. Deep transfer learning methods were employed to address these biases, which are robust to regional and environmental variations. These methods are effective due to their end-to-end learning approach, enabling them to extract relevant features directly from raw data without being significantly influenced by external factors. This ensures that the features derived are well-suited to the nature of the data, thereby mitigating the impact of regional or environmental biases on the model's performance.

The dataset consists of 1440 images in total. 70% of the dataset is allocated for training, 20% for testing, and 10% for validation. The large number of data is an important advantage in increasing the model's success. Although data augmentation techniques were not used due to the success achieved in this study, it may be possible to increase the success with various data augmentation techniques. In addition, proposing a more robust and successful model with data from new countries other than Bangladesh may be possible.

Detection and cleaning of dust accumulated on the surface of solar panels is a critical requirement to improve the efficiency of solar energy systems. The proposed AI-assisted classification and cleaning systems automate the maintenance processes of large solar farms, minimizing the need for human intervention. This results in considerable savings in terms of both time and cost. In addition, increased energy production efficiency encourages more efficient use of renewable energy sources. In particular, using deep learning models supported by transfer learning methods enables high-accuracy results with limited data. In this way, cleaning and maintenance of solar panels can be performed more efficiently, increasing the continuity and reliability of energy production. In the long term, such advanced technology applications play an important role in achieving sustainable energy goals and supporting environmental sustainability efforts.

RESULTS

This study uses ten deep transfer learning models to classify clean and dusty images in solar panels. These models are EfficientNetB3, ResNet50, MobileNet, VGG19, Xception, InceptionResNetV2, VGG16, ResNet101, DenseNet201 and EfficientNetB7. Each model is trained on clean and dusty images, and predictions are made on the test dataset. The prediction results are compared with the actual results, and the performance of each model is evaluated using criteria such as accuracy, precision, recall, and F1-Score. As a result of this evaluation, the highest accuracy rate was obtained with the ResNet101 model, at 97.92%.

After the initial results were obtained, the study aimed to improve the classification performance with the proposed ensemble learning method. For this purpose, different transfer learning methods were combined, and predictions were made using a voting method. The results obtained with this prediction approach, created by combining three combinations of three, were evaluated with accuracy, precision, recall, and F1-Score criteria. After testing all combinations, the best results were obtained with EfficientNetB3, VGG16, DenseNet201 and EfficientNetB3, ResNet101, and DenseNet201 combinations.

Based on the results of this study, a larger dataset could be recommended to improve model performance further. Integrating data from different geographical regions and weather conditions and investigating newer transfer learning models can also improve performance. Furthermore, evaluating the developed models for real-time applications can make significant contributions.

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REFERENCES

Chollet, F. (2017). Xception: Deep learning with depthwise separable convolutions. *I*EEE conference on computer vision and pattern recognition (pp. 1251-1258).

Çetin, S., Turan, E., & Bayrakdar, E. (2019). Türkiye'nin güneş enerjisi politikaları. *Third Sector Social Economic Review*, Ankara, 54(2), 949-968. http://dx.doi.org/10.15659/3.sektor-sosyal-ekonomi.19.04.1118

Canbay, Y., İsmetoğlu A., Canbay, P., (2021). Covid-19 Hastalığının Teşhisinde Derin Öğrenme ve Veri Mahremiyeti, *Mühendislik Bilimleri ve Tasarım Dergisi*, 9(2), 701-715. https://doi.org/10.21923/jesd.870263

Davaadorj, U., Yoo, K. H., Choi, S. H., & Nasridinov, A. (2021). The Soiling Classification of Solar Panel using Deep Learning. International Conference on Convergence Content, (pp. 59-60).

Dwivedi, D., Babu, K. V. S. M., Yemula, P. K., Chakraborty, P., & Pal, M. (2024). Identifying surface defects on solar PV panels and wind turbine blades using an attention-based deep learning model. *Engineering Applications of Artificial Intelligence*, 1-28, https://doi.org/10.1016/j.engappai.2023.107836.

Ferrell, D. & Anderson, E. (2023). Adapting and Generalizing Convolutional Neural Networks in Detecting Dust on Solar Panels, *preprint researchgate*, 1-6.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., ... & Adam, H. (2017). Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv preprint arXiv:1704.04861*. https://doi.org/10.48550/arXiv.1704.04861

Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4700-4708).

Kanani, P., & Padole, M. (2019). Deep learning to detect skin cancer using google colab. *International Journal of Engineering and Advanced Technology Regular Issue*, *8*(6), 2176-2183. https://doi.org/10.35940/ijeat.F8587.088619

Kaya, Y., Yiner, Z., Kaya, M., & Kuncan, F. (2022). A new approach to COVID-19 detection from X-ray images using angle transformation with GoogleNet and LSTM. *Measurement Science and Technology*, *33*(12), 124011. https://doi.org/10.1088/1361-6501/ac8ca4

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *nature*, *521*(7553), 436-444. https://doi.org/10.1038/nature14539

Maity, R., Shamaun Alam, M., & Pati, A. (2020). An Approach for Detection of Dust on Solar Panels Using CNN from RGB Dust Image to Predict Power Loss. *Cognitive Computing in Human Cognition: Perspectives and Applications*, 41-48. https://doi.org/10.1007/978-3-030-48118-6_4

Mete, S., Çakır, O., Bayat, O., Duru, D. G., & Duru, A. D. (2020). Gözbebeği hareketleri temelli duygu durumu sınıflandırılması. *Bilişim Teknolojileri Dergisi*, *13*(2), 137-144. https://doi.org/10.17671/gazibtd.563830

Onim, M. S. H., Sakif, Z. M. M., Ahnaf, A., Kabir, A., Azad, A. K., Oo, A. M. T., & Ali, M. S. (2023). Solnet: A convolutional neural network for detecting dust on solar panels. *Energies*, 16(1), 155. https://doi.org/10.3390/en16010155

Pan, S. J., & Yang, Q. (2009). A survey on transfer learning. *IEEE Transactions on knowledge and data engineering*, *22*(10), 1345-1359. https://doi.org/10.1109/TKDE.2009.191

Prabhakaran, S., Uthra, R. A., & Preetharoselyn, J. (2023). Deep Learning-Based Model for Defect Detection and Localization on Photovoltaic Panels. *Computer Systems Science and Engineering*, *44*(3), 2683-2700. http://dx.doi.org/10.32604/csse.2023.028898

Saqlain, M., Jargalsaikhan, B., & Lee, J. Y. (2019). A voting ensemble classifier for wafer map defect patterns identification in semiconductor manufacturing. *IEEE Transactions on Semiconductor Manufacturing*, 32(2), 171–182. https://doi.org/10.1109/TSM.2019.2904306

Selvi, S., Devaraj, V., Prabha, R. P. S., & Subramani, K. (2023). Detection of Soiling on PV Module using Deep Learning. *SSRG International Journal of Electrical and Electronics Engineering*, 10(7), 93-101. https://doi.org/10.14445/23488379/IJEEE-V10I7P108

Sewell, M. (2008). Ensemble learning. *RN*, *11*(02), 1-34.

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*. https://doi.org/10.48550/arXiv.1409.1556

Sokolova, M., Japkowicz, N., & Szpakowicz, S. (2006, December). Beyond accuracy, F-score and ROC: a family of discriminant measures for performance evaluation. Australasian joint conference on artificial intelligence (pp. 1015-1021). https://doi.org/10.1007/11941439_114

Szegedy, C., Ioffe, S., Vanhoucke, V., & Alemi, A. (2017, February). Inception-v4, inception-resnet and the impact of residual connections on learning. Thirsty-First AAAI conference on artificial intelligence, (pp. 4278-4284) https://doi.org/10.1609/aaai.v31i1.11231

Şenol, A., Canbay, Y., & Kaya, M. (2021). Trends in Outbreak Detection in Early Stage by Using Machine Learning Approaches. *Bilişim Teknolojileri Dergisi*, *14*(4), 355-366. https://doi.org/10.17671/gazibtd.878089

Tan, M., & Le, Q. (2019). Efficientnet: Rethinking model scaling for convolutional neural networks. International conference on machine learning (pp. 6105-6114).

Utku, A., & Akcayol, M. A. (2024). Spread patterns of COVID-19 in European countries: hybrid deep learning model for prediction and transmission analysis. *Neural Computing and Applications*, 36, 10201–10217. https://doi.org/10.1007/s00521-024-09597-y

Yarğı, V., & Postalcıoğlu, S. (2021). EEG işareti kullanılarak bağımlılığa yatkınlığın makine öğrenmesi teknikleri ile analizi. *El-Cezeri*, 8(1), 142-154. https://doi.org/10.31202/ecjse.787726

Zyout, I. & Oatawneh, A. (2020), February. Detection of PV solar panel surface defects using transfer learning of the deep convolutional neural networks. Advances in Science and Engineering Technology International Conferences (ASET), (pp. 1-4). https://doi.org/10.1109/ASET48392.2020.9118384