SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V10I7P108

Volume 10 Issue 7, 93-101, July 2023

Original Article

Detection of Soiling on PV Module using Deep Learning

S. Selvi[1], V. Devaraj[2], Rama Prabha. P.S[3], Kavitha Subramani[4]

[1,2,3]Electrical and Electronics Department, Panimalar Engineering College, Tamilnadu, India.
[4]Computer Science Engineering Department, Panimalar Engineering College, Tamilnadu, India.

[1]Corresponding Author : selviselvaraj@gmail.com

Received: 30 April 2023 Revised: 28 June 2023 Accepted: 19 July 2023 Published: 31 July 2023

Abstract *- As a clean and sustainable energy source, solar energy is gaining popularity quickly and surpassing other generation methods. However, the accumulation of dirt on the surface of Photovoltaic panels (PV) is a significant barrier to harvesting solar energy. The panel's performance and energy output are negatively impacted by this soiling, which drastically reduces the panel's capacity to harvest sunlight effectively. Therefore, regular PV module cleaning is essential to minimise efficiency losses and maximize income during the system. In this work, an intelligent approach for monitoring soiling on PV panels utilising cutting-edge Artificial Intelligence (AI) methods in order to solve this problem. As AI continues to gain popularity and become an essential component of technological advancements, we employ a predictive maintenance strategy using deep learning for soiling. Our method utilizes real-time data collection and testing, unlike existing models requiring high computational power. We achieved similar results by comparing our approach to state-of-the-art computer vision architectures while significantly reducing computational costs. Experimental results demonstrate an impressive accuracy rate of 97% in classifying solar panels' soiling status. This indicates excellent performance in identifying when panels require cleaning. Therefore, our proposed method can help maintenance personnel determine optimal cleaning schedules for PV systems. By minimizing power loss and saving labour and time associated with long-term maintenance, our approach offers tangible benefits to the overall operation and efficiency of PV systems.*

Keywords *- Photovoltaic module, Soiling, Deep learning, Convolutional Neural Network, Cleaning.*

1. Introduction

The world's energy consumption is currently at an all-time high, and in the coming decades, more rise is anticipated. Fossil fuels and other non-renewable energy sources quickly deplete natural resources and produce about 80% of the world's energy. It is anticipated that the rate of resource extraction will increase, which could result in an impending energy crisis. Traditional fossil fuel consumption also substantially negatively impacts our ecosystem because it increases the generation of hazardous greenhouse gases (GHG). [1].

The growing demand for clean energy has made the transition to renewable energy the primary energy source possible [2-4]. Most renewable energy sources are found naturally and are essentially free [5–7], in contrast to the expensive extraction, handling, and distribution of fossil fuels. Renewable energy sources are also stable, affordable, and long-lasting [8]. Water, wind, and solar energy are the primary renewable natural resources that can generate sustainable energy [8]. The third-largest contributor is solar energy, behind hydro and wind power. The possibility of solar energy to supply clean and sustainable electricity has boosted the attention on solar power globally.

Solar cells built of semiconductors are used in photovoltaic (PV) technology to collect solar radiation and transform it into electrical energy [8]. The location of the solar plant significantly impacts the efficiency and efficacy of solar photovoltaic panels and the amount of energy produced [10].

Standard test conditions (STC), which include an irradiance level of 1000 W/m2, an AM 1.5 solar spectrum, and a module temperature of 25°C[10], are typically used to assess a PV module's performance. However, these conditions are uncommon in real-world situations because of several environmental and climatic factors[10–13]. Among these factors, soiling is caused by the accumulation of dirt and dust on the surface of solar PV panels.

The Mine Safety and Health Administration (MSHA) defines dust as a small, solid particle originating in the atmosphere and undergoing no physical or chemical changes beyond breaking [14]. These particles are available in various shapes, sizes, volumes, and chemical make-ups. In addition, different particle kinds correspond to different geographical regions and local activities.

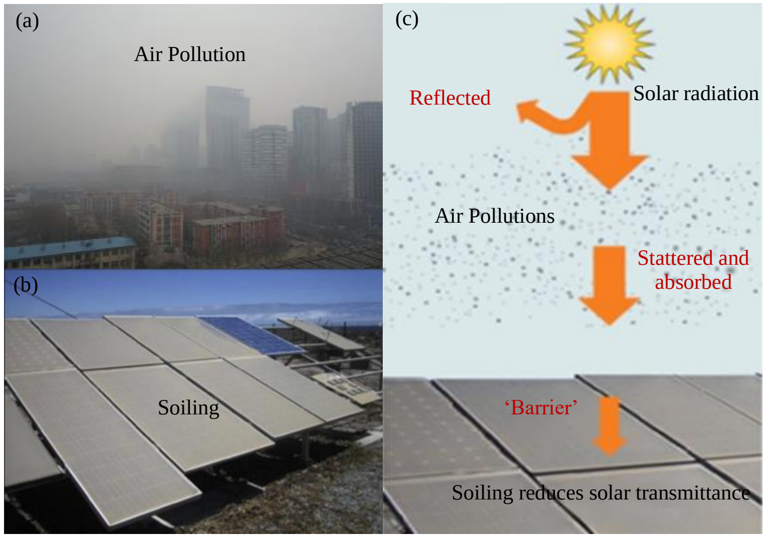


Fig. 1 Shows how air pollution and soiling reduce solar radiation [12-13]

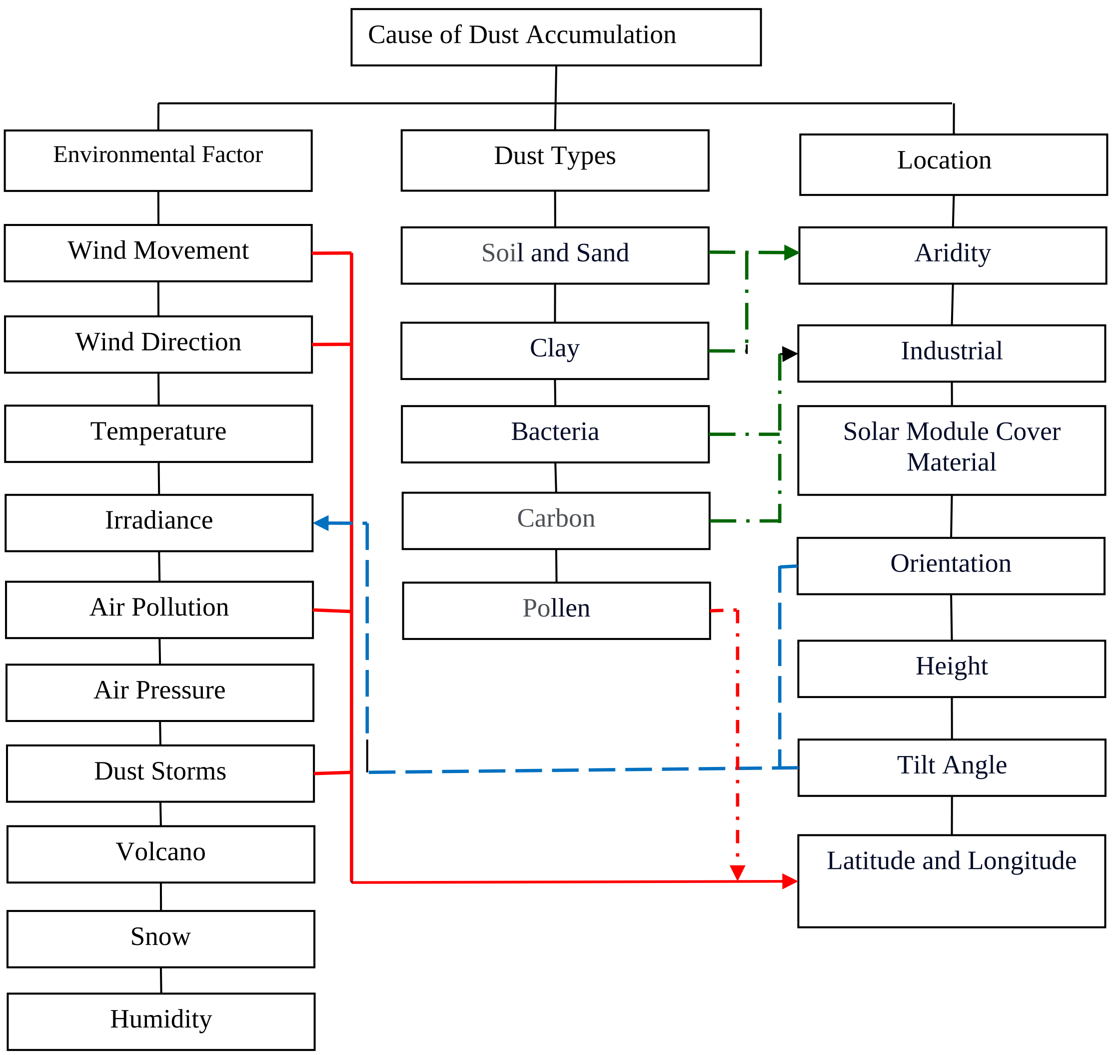


Fig. 2 Various causes of dust accumulation [14]

The process through which dirt, dust, and pollution are deposited and accumulate on the surface of a solar PV module is called "soiling" [11].This degrades the overall performance efficiency by reflecting, absorbing, and scattering light, creating harmful optical disturbances to the solar PV cell's solar irradiance transmittance [11-16]. After solar radiation passes through the soiling layer, only a tiny portion can reach the solar cell shown in Figure 1. This reduces the solar cell's ability to generate electricity, decreasing overall power efficiency [17]. Besides irradiation and temperature, dust buildup is the third most significant component affecting solar PV module performance. Since soiling intensity varies with geographic location and seasonal climatic conditions, it is difficult to generalise the loss level brought on by soiling on a PV module [18].

The extent of this soiling effect was most significant in regions with a high dust frequency and a low precipitation rate. In regions without rainfall, the buildup of dirt on solar panels can significantly impact the extent to which PV modules work. Mainly, soil accumulation status varies from region to region[24]. The various forms of dust are shown in Figure 2. The perceived benefit of PV systems declines as a result. In desert regions, the accumulation of soiling on PV modules may even result in a 40% reduction in the electrical power produced by PV systems. Nevertheless, a steady power loss of between 3% and 4% was caused by this issue[24-25]. But with proper cleaning, it is claimed that 25% energy recovery is possible in PV modules [25]

In order to maintain PV systems efficiently, more research on the accumulation of dust is essential. If efficiency continues to drop, PV systems risk losing their appeal as an alternative energy source, especially for large solar farms. In this case, sustaining solar plants depends on keeping the PV modules clean. It has been demonstrated that cleaning can prevent PV systems from losing power. However, cleaning involves a lot of time and money. To make it cost-effective, optimized cleaning techniques should be evolved.

Predictive maintenance will be emphasised in addition to methods for reducing efficiency losses caused by dust accumulation. The employment of sophisticated monitoring systems and data analysis is called "predictive maintenance" of dust in solar panels. It is necessary to use sensors or monitoring systems that continuously monitor parameters like energy output, temperature changes, or surface reflectivity. By analysing the information collected to find trends and patterns, it is possible to determine the dust deposition rate and how it affects the panel's performance. Predictive maintenance systems may employ statistical models or machine learning algorithms to ascertain the ideal time to clean the panels. Machine learning algorithms can analyse images of PV panels to determine where and how much soiling has occurred. By developing models on an extensive dataset of annotated images and videos, algorithms can be trained to recognise different types of soiling, such as dust, dirt, or debris.

As a result, soiling levels can be properly and automatically checked without manual intervention. The recent progress of AI-based dust detection systems has opened up new vistas and increased their popularity [31]. For the classification and detection of dusty panels, scientists have used various methods, such as random forest, k-nearest neighbours (k-NN), and the measurement of the size of dust particles using computer vision for high-resolution images [32, 33].

While previous studies have focused only on soil detection, this study expands the analysis to encompass four different types of dust. This work uses an image analysis approach using deep learning methods to detect and quantify the different types of dust, including brown soil, white soil, leaves, and bird droppings, on photovoltaic (PV) panels. An evaluation method is presented that compares the actual and predicted values, using the absolute error as a measure. Overall, the study offers a comprehensive framework for analyzing and quantifying dust on PV panels using image analysis and deep learning techniques.

Researchers and engineers can create automated systems that can effectively and reliably detect dust on PV panels using these machine-learning techniques, enabling prompt maintenance and increasing the effectiveness of energy production.

Fig. 3 PV panel used part of the work

2. Methodology

2.1. Data Collection

An early data collection phase involved a six-month attempt to collect data to find dust on a 15-kW PV system installed on the institute campus. There are 300 images and videos in total in the dataset. In this dataset, half of the samples (200 have been classified as "clean," indicating that there is no dust present, while the other half (100) have been classified as "soiled," indicating that there is dust accumulation. Figure 3 shows a sample panel used in the work.

2.2. Data Preprocessing

The primary objective of data preprocessing is revolved around extracting vital information from the images and classifying them based on the presence of dust. After their classification, we renamed the original images to facilitate easier handling and organisation. We are renaming the data to simplify the subsequent stages of analysis and processing.

2.2.1. Segmentation

The next step involves the segmentation of soiling on the panels, which can be done using modern deep learning or computer vision techniques. Segmentation involves two steps. The first step is to detect the solar panel and draw a bounding box around the panel. The next step is to Segment the pixels inside the bounding box into soiling and solar panel pixels. Using the traditional computer vision algorithm like Canny edge detector and Hough transforms to find the bounding box.

Using this technique, the edge of the solar panel can be detected in rectangular form. However, the computation cost is more. While doing segmentation, also many problems arised. If the current image only contains solar panel regions, a small number of solar pixels can be recovered, the RGB colour space can be assumed, and what is not solar pixels may be classified using an if-else condition. It is a solar panel pixel if the pixel value is inside the authorised blue range; else, it is a soil pixel. In addition to having blue pixels, solar panels have white lines across their surface, which throws off our current colour model. To overcome all these difficulties, a deep learning model is used to find soiling on solar panels.

2.2.2. Labelling

Labelling is the procedure used to provide this ground truth data, which is the data that accurately describes the objects contained in the images or videos, which is used to train the neural network. There are several techniques for labelling a dataset; labelling at the pixel level becomes essential in our work. So semantic segmentation is used. A special kind of network called a Convolutional network is used for segmentation. Moreover, it is shown in Fig 4.

2.2.3. Image Augmentation

The training data the neural network has been exposed to has a significant role in its capacity to produce accurate outputs from new data it encounters. However, one major hurdle is the lack of accessible, representative, and diverse training data. In terms of object perspectives, sizes, and colour combinations, datasets frequently display monotony. For instance, there are different sizes of solar panels, and images taken of them may differ based on the angle, distance from the camera, and other factors. As a result, a model developed with such repetitive data will only be helpful for data of that kind, giving rise to the problem known as model overfitting. Therefore, when the model encounters fresh data with higher variability, it tends to have insufficient inference performance, yielding inaccurate outcomes.

2.2.4. Setting Up a Network

The dataset must be processed through several processes before being fed into the neural network. The two main methods are building a neural network from scratch or utilising a pre-trained network. In the first method, the initialization of the weights and biases in a neural network is random. A network must be trained often to acquire the desired accuracy and optimise these parameters.

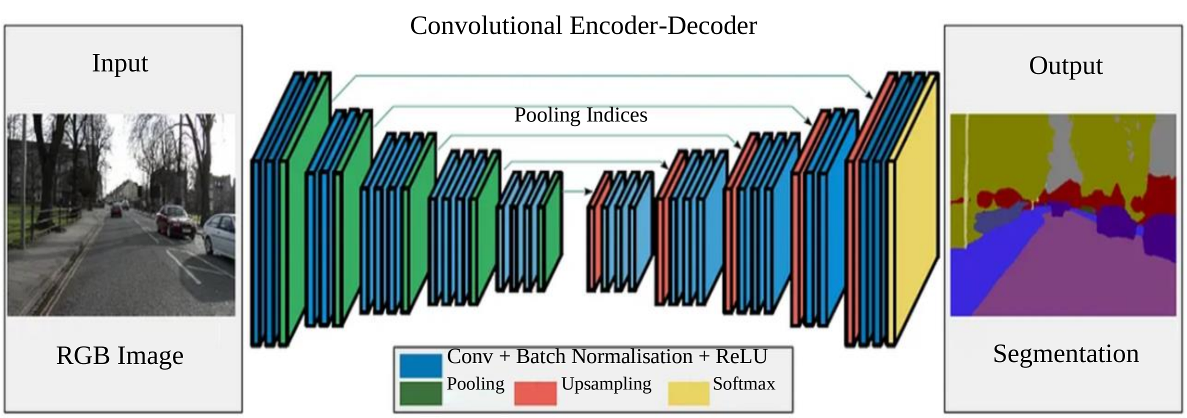


Fig. 4 Encoder-decoder architecture [21]

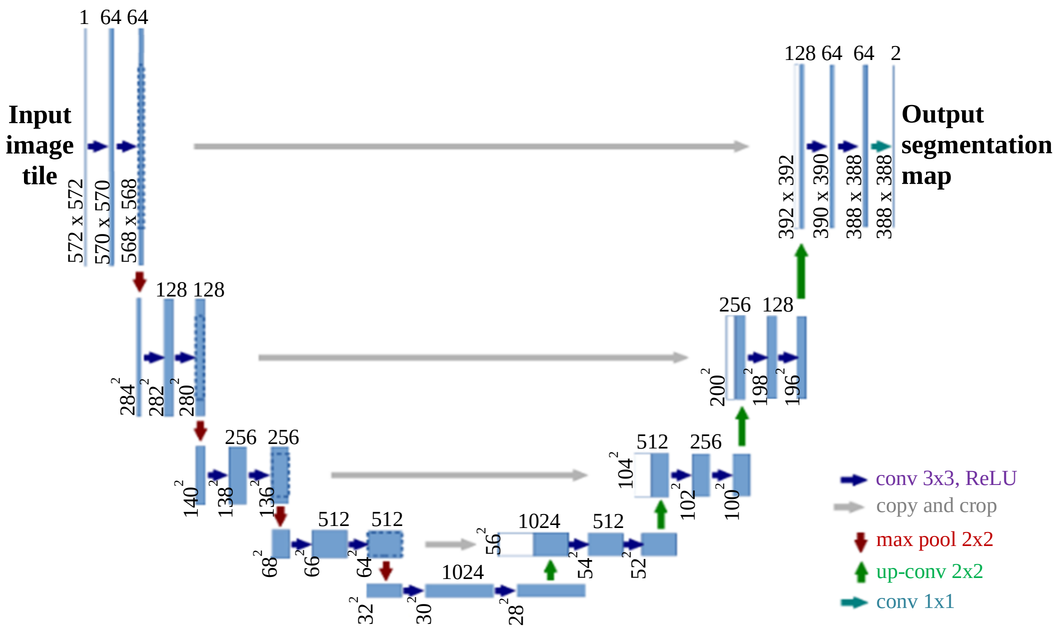
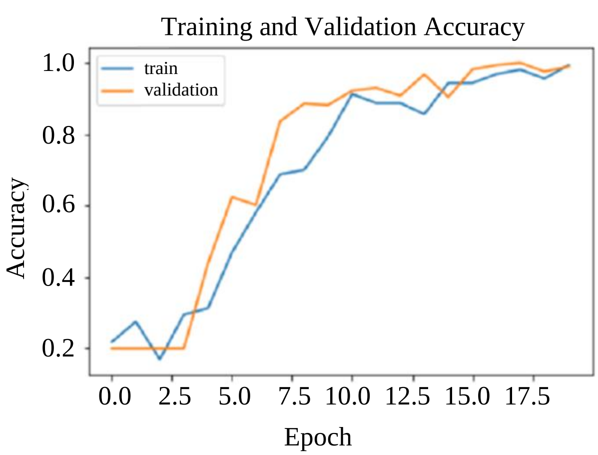


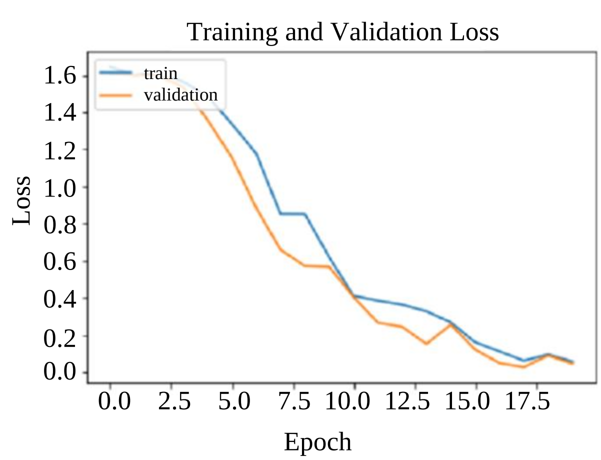
Fig. 5 Framework of U-net architecture for semantic segmentation [35]

This method, however, might be time-consuming and computationally expensive. A more workable alternative is to use a network that has already been trained. As trained on extensive datasets, pre-trained networks have optimised values for weights, biases, and other hyperparameters. These networks have already acquired valuable representations of different visual properties, which can be helpful for a particular job. The neural network can achieve higher accuracy with a substantially smaller number of training iterations by using a pre-trained network since it can draw on the information and learnt characteristics from the prior training. Time and computing resources are saved in this method.

The MobileNetV2 pre-trained network was used in the context of this study. A famous pre-trained network architecture called MobileNetV2 is renowned for its effectiveness and precision in various computer vision tasks. Using MobileNetV2 as the base network, optimised weights, biases, and other hyperparameters can facilitate quicker convergence and more accuracy for the particular task. To detect features, neural networks often downsample the input images. However, we must upsample the image if we want the output to be a segmented image of the same size as the input. A downscaled image is taken and returned to its standard size using a reversed pre-trained network to do this. This is called encoder-decoder architecture, shown in Fig 5.



(a) Accuracy



(b) loss

Fig. 6 Accuracy and loss

Fig. 7 Snippet of dust classification

In neural networks, downsampling can lead to data loss, lowering the output's quality. This problem was addressed through the development of the U-Net architecture. By saving data during the downsampling process and utilising it during the upsampling, it maintains the quality of the data. This data is relayed back into the neural network's decoder section through skip connections. Through these links, the network can access and use the data that has been saved, resulting in the creation of higher-quality output.

The images were taken in the same place and attitude after carefully studying the information. This indicates that there is not much variation in the dataset's perspectives and environmental conditions. Additionally, the dataset captures the progressive buildup of soiling over weeks, which may result in overfitting if the model is trained only to recognise the gradual buildup rather than the actual soiling patterns. In addition, we observed that the dataset's class distribution was unbalanced. Remarkably, there were only 100 brown-soiled images and about 200 clean. Due to the model's potential bias towards the majority class and difficulty correctly classifying the minority class, this imbalance can provide difficulties during training.

We accomplished satisfactory results because we started with a pre-trained network and a minimal dataset of 50 images with classes like clean, brown sand, white sand, bird droppings, leaf and background. To enhance the model's performance, we carefully tuned several hyperparameters, including the quantity of data, epochs, and other pertinent settings. It is crucial to remember that utilising many samples and conducting the training for many epochs can result in overfitting, where the model becomes overly tailored to the training data and struggles to generalise well to new, unforeseen data. As a result, we were careful to strike a balance and prevent overfitting by ensuring the model does not become unduly reliant on its memory of the training examples. Amazingly, the entire training procedure only took 10 minutes, demonstrating the method's effectiveness and efficiency.

The identification of solar panels yielded results nearly in line with the stated objectives, showing that the model could correctly categorise and predict the labels of the validation dataset. The model's effectiveness and capacity to accurately recognise and assign labels to solar panels are demonstrated in the accompanying images, which visually represent the genuine labels and predicted labels in the validation dataset. These findings offer a positive indicator of the model's ability to accomplish the necessary goals. The mean intersection over union (MIoU) metric provided a distinct viewpoint despite the predictions for solar panel identification looking positive visually. The MIoU metric, which is frequently used to assess semantic image segmentation tasks, revealed that, with an increase of only up to 14%, overall performance did not considerably improve throughout training.

The MIoU metric thoroughly assesses segmentation accuracy by calculating the overlap between predicted and ground truth segmentation masks for various classes. The MIoU scores in this instance showed only modest improvement in the model's ability to correctly segment the several classes, despite the initial positive visual results. The validation accuracy decreased when training increased, indicating that the model was overfitting. Overfitting is when a model memorises the training instances too thoroughly, which results in poor generalisation of new data. This problem was caused by the unbalanced class distribution, as there were far less soiled pixels than panel and background pixels. This imbalance may have prevented the model from learning and correctly classifying the dirty pixels, resulting in subpar performance and overfitting. In order to enhance the model's functionality and produce better segmentation results for all classes, these insights point to the need for additional research and possible ways to address the class imbalance issue.

Although it might perform well on the validation dataset, we need generalisation to new and arbitrary solar panel images. The prediction is shown on a random solar panel outside the dataset in the image below. It is important to note that the effectiveness of the deep learning approach depends on the quality and diversity of the dataset, as well as the selection and fine-tuning of the model. Regular model retraining may be necessary to handle variations in dust patterns, lighting conditions, or panel design.

3. Results and Discussion

The work aimed to create an AI system to identify solar panel soiling in sizable solar farms. In videos with diverse characteristics, the trained neural network performed well in identifying solar panels, with an accuracy of about 97%, as shown in Figure 7. From the figure, after 20 epochs, the validation loss is 9.7%. However, it had trouble locating small areas of soil on the panels. The output from the CNN was highly dependent on the quality of training images. Since the image quality was inadequate, it could not detect mild soiling layers. Another significant challenge encountered throughout the segmentation operation was class imbalance. We have many pixels for categorising the solar panels and background; however, there are comparably few for the brown and white soiled sections. When training, the network attempts to learn despite infrequently detecting soil on the studied images.

For instance, with White dust, the network could not distinguish between white junction points and the dust itself. The second problem was that just a few varieties of dust, like white and brown, were included in our dataset. Since there may be additional causes for soiling, such as bird shit, they must also be considered when training the network. The data set contained samples with static location and angle coordinates, which minimised internal variation. Hence, there is no inherent variability even after augmentation, which is terrible for training neural networks. Figure 7 shows the snippet of soil classification.

4. Conclusion

Accuracy by itself, however, does not serve as an all-inclusive statistic for image segmentation tasks. The mean intersection over union (IoU) statistic, which assesses semantic segmentation, remained at 14 percent despite the substantial decrease in loss. This suggests that further work must be done to enhance the model's ability to segment and define soiling patterns appropriately. The optimal number of images per class is currently being researched, and our present dataset only has 50 images per class. Analysing the network's efficiency based on the F1 score may yield insightful, helpful information for improving network efficiency.

Although the down-stack portion of the network has not yet been trained, doing so could lead to better outcomes. Class imbalance needs to be addressed, and it can be done so by adopting a proper loss function that gives the minority classes more weight throughout training. Labelling light dust on solar panels can also improve the network's capacity to detect soiling more effectively. The network may be trained to recognise and recognise various levels of soiling on solar panels with the help of this additional level of annotation, which offers useful information.

References

[1] Efstratios Chaniotakis, "*Modelling and Analysis of Water-Cooled Photovoltaics*," University of Strathclyde, 2001. [Google Scholar] [Publisher Link]

[2] S. Bowden et al., "High-Efficiency Photovoltaic Roof Tiles with Static Concentrators," *Proceedings of 1994 IEEE 1st World Conference on Photovoltaic Energy Conversion – WCPEC*, vol. 1, pp. 774-777, 1994. [CrossRef] [Google Scholar] [Publisher Link]

[3] Becker H, "Reduced Output of Solar Generators Due to Pollution," *14th European Photovoltaic Solar Energy Conference*, 1997. [Google Scholar] [Publisher Link]

[4] Elias Urrejola et al., "Effect of Soiling and Sunlight Exposure on the Performance Ratio of Photovoltaic Technologies in Santiago, Chile," *Energy Conversion and Management*, vol. 114, pp. 338–347, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[5] Wesam Raddad et al., "*The Recent Cleaning Techniques in Solar PV*," An-Najah National University, 2019. [Google Scholar] [Publisher Link]

[6] Jane Palmer, "Smog Casts a Shadow on Solar Power," *Engineering*, vol. 5, pp. 989–990, 2019. [CrossRef] [Publisher Link]

[7] P. Rajadurai, "Cyber Security in Wind Energy Generation via Deep Learning," *SSRG International Journal of Computer Science and Engineering*, vol. 9, no. 12, pp. 1-6, 2022. [CrossRef] [Publisher Link]

[8] Christian Schill, Stefan Brachmann, and Michael Koehl, "Impact of Soiling on IV-Curves and Efficiency of PV-Modules," *Solar Energy*, vol. 112, pp. 259–262, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[9] Mohammad Reza Maghami et al., "Power Loss Due to Soiling on Solar Panel: A Review," *Renewable and Sustainable Energy Reviews*, vol. 59, pp. 1307–1316, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[10] Zeki Ahmed Darwish et al., "Effect of Dust Pollutant Type on Photovoltaic Performance," *Renewable and Sustainable Energy Reviews*, vol. 41, pp. 735-744, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[11] Yusuf N Chanchangi et al., "Dust and PV Performance in Nigeria: A Review," *Renewable and Sustainable Energy Reviews*, vol. 121, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[12] Jim J John, "Study of Soiling Loss on Photovoltaic Modules with Artificially Deposited Dust of Different Gravimetric Densities and Compositions Collected from Different Locations in India," *IEEE Journal of Photovoltaics*, vol. 6, no. 1, pp. 236-243, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[13] Lawrence L Kazmerski et al., "Fundamental Studies of Adhesion of Dust to PV Module Surfaces: Chemical and Physical Relationships at the Microscale," *IEEE Journal of Photovoltaics*, vol. 6, no. 3, pp. 719-729, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[14] Ali Al Shehri et al., "Impact of Dust Deposition and Brush-Based Dry Cleaning on Glass Transmittance for PV Modules Applications," *Solar Energy*, vol. 135, pp. 317-332, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[15] Suellen C S Costa, Antonia Sonia A C Diniz, and Lawrence L Kazmerski, "Dust and Soiling Issues and Impacts Relating to Solar Energy Systems: Literature Review Update for 2012–2015," *Renewable and Sustainable Energy Review*, vol. 63, pp. 33-61, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[16] Suellen C S Costa, Antonia Sonia A C Diniz, and Lawrence L Kazmerski, "Dust and Soiling R&D Progress: Literature Review Up Date for 2016," *Renewable and Sustainable Energy Reviews*, vol. 82, pp. 2504-2536, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[17] Arash Sayyah, Mark N Horenstein, and Malay K Mazumder, "Energy Yield Loss Caused by Dust Deposition on Photovoltaic Panels," *Solar Energy*, vol. 107, pp. 576-604, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[18] Zeki Ahmed Darwish, "Impact of Some Environmental Variables with Dust on Solar Photovoltaic: Review and Research," *International Journal of Energy and Environment*, vol. 7, no. 4, pp. 152–159, 2013. [Google Scholar]

[19] Benjamin Figgis, "Review of PV Soiling Particle Mechanics in Desert Environments," *Renewable and Sustainable Energy Reviews*, vol. 76, pp. 872-881, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[20] Sanaz Ghazi, Ali Sayigh, and Kenneth Ip, "Dust Effect on Flat Surfaces - A Review Paper," *Renewable and Sustainable Energy Reviews*, vol. 33, pp. 742-751, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[21] Olaf Ronneberger, Philipp Fischer, and Thomas Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," *Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, vol. 9351, pp. 234-241, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[22] Monto Mani, and Rohit Pillai, "Impact of Dust on Solar Photovoltaic (PV) Performance: Research Status, Challenges and Recommendations," *Renewable and Sustainable Energy Reviews*, vol. 14, no. 9, pp. 3124-3131, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[23] Mohammad Reza Maghami et al., "Power Loss Due to Soiling on Solar Panel: A Review," *Renewable and Sustainable Energy Reviews*, vol. 59, pp. 1307-1316, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[24] Athar Hussain, Ankit Batra, and Rupendra Pachauri, "An Experimental Study on the Effect of Dust on Power Loss in Solar Photovoltaic Module," *Renewables: Wind, Water, and Solar*, vol. 4, no. 9, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[25] P. A. Patil, J. S. Bagi, and M. M. Wagh, "A Review on Cleaning Mechanism of Solar Photovoltaic Panel," *International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS)*, pp. 250-256, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[26] C. Igathinathane et al., "Machine Vision Based Particle Size and Size Distribution Determination of Airborne Dust Particles of Wood and Bark Pellets," *Powder Technology*, vol. 196, no. 2, pp. 202–212, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[27] Julien Maitre, Kévin Bouchard, and L. Paul Bédard, "Mineral Grains Recognition using Computer Vision and Machine Learning," *Computers & Geosciences*, vol. 130, pp. 84-93, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[28] Andrea Proietti et al., "Dust Detection and Analysis in Museum Environment Based on Pattern Recognition," *Measurement*, vol. 66, pp. 62–72, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[29] Alejandro Rico Espinosa, Michael Bressan, and Luis Felipe Giraldo, "Failure Signature Classification in Solar Photovoltaic Plants using RGB Images and Convolutional Neural Networks," *Renewable Energy*, vol. 162, pp. 249-256, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[30] Yao Guangle, Lei Tao, and Zhong Jiandan, "A Review of Convolutional-Neural-Network-Based Action Recognition," *Pattern Recognition Letters*, vol. 118, pp. 14-22, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[31] Rahul Kavi et al., "Multiview Fusion for Activity Recognition using Deep Neural Networks," *Journal of Electronic Imaging*, vol. 25, no. 4, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[32] Humble Po-Ching Hwang et al., "Detection of Malfunctioning Photovoltaic Modules Based on Machine Learning Algorithms," *IEEE Access*, pp. 37210-37219, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[33] Gargi Sharma, and Gourav Shrivastava, "Crop Disease Prediction using Deep Learning Techniques - A Review," *SSRG International Journal of Computer Science and Engineering*, vol. 9, no. 4, pp. 23-28, 2022. [CrossRef] [Publisher Link]

[34] Kamal Adel Abuqaaud, and Azzeddine Ferrah, "A Novel Technique for Detecting and Monitoring Dust and Soil on Solar Photovoltaic Panel," *Advances in Science and Engineering Technology International Conferences (ASET)*, pp. 1-6, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[35] Abolfazl Abdollahi, Biswajeet Pradhan, and Abdullah M. Alamri, "An Ensemble Architecture of Deep Convolutional Segnet and Unet Networks for Building Semantic Segmentation from High-Resolution Aerial Images," *Geocarto International*, vol. 37, no. 12, pp. 3355-3370, 2020. [CrossRef] [Google Scholar] [Publisher Link]