ARTIFICIAL NEURAL NETWORK BASED APPROCH FOR CLASSIFICATION OF FAULTS IN PHOTOVOLTAIC ARRAYS

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ABSTRACT

A photovoltaic array (PV array) is a group of solar panels that are electrically linked together to generate more electricity. PV arrays can be used to generate electricity for the grid as well as to power residences. Since they have a minimal impact on the environment, they are becoming a more and more popular source of renewable energy. The accurate and timely detection of faults like Electric damages, Physical damages, and soiling in photovoltaic (PV) arrays is crucial for ensuring the efficient operation and maintenance of solar energy systems. Here, we propose a methodology for fault classification in PV arrays using Artificial Neural Networks (ANN), Voting classifier and Convolutional Neural Networks (CNN) to classify 6 distinct anomalies commonly found in PV arrays, including Dusty, electrical damage, physical damage, bird drop, snow covered and clean. An ANN architecture and a voting classifier is designed for binary classification, allowing for the detection of faults. A CNN model is built for the efficient classification of the faults. This result contributes to the development of automated fault detection systems in the solar energy industry, facilitating efficient maintenance planning and enhancing the reliability and efficiency of photovoltaic arrays.

Keyword : - *Artificial neural network, Convolutional Neural Network, Photovoltaic Arrays, Fault classification, Solar panel, Voting classifier*

1. INTRODUCTION

Photovoltaic (PV) arrays have emerged as one of the most promising sources of renewable energy, making significant contributions to sustainable electricity generation. Their proliferation is largely due to their eco-friendliness, low operating costs, and the ever-increasing demand for clean energy alternatives. Solar panels or photovoltaic (PV) arrays are collections of solar cells that work together to transform sunlight into electricity. These arrays are a crucial part of solar photovoltaic systems and are employed to capture solar energy for a variety of uses, primarily the production of electricity. Photovoltaic (PV) arrays may encounter a variety of flaws or problems that may impair their dependability and performance. The efficiency and security of a solar power system must be maintained by quickly identifying and fixing these problems.

Here are some typical PV array fault types:

Accumulation of dirt, dust, or other debris can lessen the quantity of sunlight that reaches the cells, which will result in less energy being produced. In order to lessen this problem, regular cleaning is required. Causes of Dust and Dirt Buildup are due to organic environmental elements like wind-blown dust, pollen, leaves, and other airborne particles, dust and filth can accumulate on PV panels over time. Depending on where the PV system is located, the amount of dirt and dust buildup may vary. Climates that are dry and arid are more likely to have problems with dust.

- Cracked or Damaged Panels: PV panels' efficiency can be affected by physical deterioration such as cracks or breakage. A regular check might help find damaged panels and replace them. This includes physical damages in the solar panels

- Environmental Factors: Severe weather events like hail, snow, hurricanes, and floods can harm solar panels and related equipment, which can cause system errors. Snow buildup on solar panels may prevent sunlight from reaching the cells, lowering energy output. Heavy snowfall can also put strain on the roof or mounting structure, possibly resulting in structural damage. These problems can be reduced by routine snow removal or devices with self-cleaning features.

- Photovoltaic (PV) arrays may sustain electrical damage for a number of reasons, which could result in performance degradation, safety risks, or system errors. Arc faults and ground faults are two typical electrical circuit malfunctions that can lead to electrical damage and fire risks to PV arrays. These errors in PV systems can be found and avoided with the use of arc fault circuit interrupters (AFCIs) and ground fault circuit interrupters (GFCIs).

However, for PV arrays to remain a reliable energy source, it is imperative to ensure their proper functioning, which includes timely detection and classification of faults or anomalies that might impede their performance. PV array efficiency is vulnerable to several defects, including hotspots, shading, soiling, degradation, and module failures. Reduced energy output, higher maintenance costs, and even significant safety risks can result from these problems. Accurate and prompt fault categorization is crucial to reducing these issues and maintaining the efficiency of PV systems. In PV arrays, traditional fault detection techniques frequently rely on manual inspection or simple rule-based algorithms. These methods have restrictions on accuracy, scalability, and effectiveness. There is an increasing demand for more sophisticated and automatic fault detection and classification approaches as PV installations get bigger and more complicated. Modern fault detection techniques for PV arrays frequently lack the accuracy needed to detect subtle and complicated defects. Rule-based algorithms could miss anomalies that do not follow predetermined rules, while manual inspections can be time-consuming, labor-intensive, and unreliable. Additionally, traditional techniques are less effective for remote monitoring and large-scale PV installations, where real-time defect identification and categorization are crucial.

The main objective of PV arrays is the efficient production of electricity. Over time, even small flaws have a big effect on energy output. As a result, timely identification and correction of problems can assist maintain high energy efficiency. Installations of PV arrays must priorities safety. Hotspots and other faults can increase the risk of fire, while other abnormalities could damage equipment. Safety risks and expensive equipment breakdowns can be avoided by promptly identifying and classifying defects. PV systems are expensive investments, and their lifecycle costs may include large maintenance costs. Through the facilitation of focused and timely interventions, effective fault categorization can lower maintenance costs. Automated, scalable, and remote monitoring solutions are crucial due to the size and complexity of PV installations increasing. Modern fault classification techniques should be distant detectable and scalable to different system sizes. This project intends to build a hybrid artificial intelligence (AI)-based strategy to address the current flaws in fault classification for PV arrays. By creating a comprehensive solution that combines the strength of artificial intelligence (AI) and deep learning techniques, the suggested work aims to close the gaps in fault classification technologies that are now present. In summary, this research addresses the challenges of fault detection and classification in PV arrays by proposing an innovative solution that integrates AI and deep learning techniques. The subsequent sections of this work will delve into the methodology, results, and discussions, providing a comprehensive analysis of the project's findings and implications.

2. LITERATURE REVIEW

Ramón Fernando et al (2021) have given the solution entails training two artificial neural network models, the first of which is a binary classifier that determines if a fault exists or not, and the second of which is a multiclass classifier that determines the type of fault. In an architecture of nine photovoltaic panels connected in a matrix with three rows and three columns (which can be expanded to bigger systems), the resultant models were trained using simulation data. The study reveals a 92.95% overall accuracy for the prediction method.

Farkhanda Aziz et al (2020) Have given a cutting-edge method that effectively detects and categorizes PV system defects by using deep two-dimensional (2-D) convolutional neural networks (CNN) to extract characteristics from 2-D scalograms produced from PV system data. With a high fault detection accuracy of 73.53%, it is seen that the suggested method using adjusted pre-trained CNN surpasses existing techniques.

Samah Laamami et al (2017) Used an artificial neural network to classify faults. The system under study consisted of a PV array with the Perturb and Observe (P&O) maximum power point tracking (MPPT) technique implemented utilizing a boost converter. MATLAB/SIMULINK software was used to complete the simulation. The PV system has five separate flaws in place. The network was constructed and trained using the neural network fitting tool, and its performance was assessed using regression analysis and mean square error (MSE).

Sunil Rao et al(2021) Developed a number of specially designed neural networks for the detection and categorization of solar array problems were developed. utilized criteria like accuracy, confusion matrices, and the Risk Priority Number (RPN) to assess defect etection and categorization. Using bespoke neural networks with dropout regularizes was examined and evaluated. By recognizing and diagnosing eight distinct defects and often recurring circumstances that affect power output in utility scale PV arrays, their method promises to increase efficiency.

Swathika et al(2022) In this work, an artificial neural network-based fault classification method for photovoltaic systems is given. This defect detection system was created in the MATLAB/ SIMULINK environment using a neural fitting tool. Voltage and current measured in real-time were the metrics taken into consideration. This technique examines the Photovoltaic system's panel-level faults. It is possible to determine the type of fault by analyzing the current and voltage.

Selma Tchoketch et al(2021) The data-feeding stage, the fault-modeling step, and the decision step were the three primary components of the suggested methodology. The initial phase entails supplying the neural networks with actual meteorological and electrical data, such as sun irradiation, panel temperature, photovoltaic current, and photovoltaic voltage. In the second step, two networks of artificial neural networks are used to mimic a healthy mode of operation along with five additional defective operating modes. Six classes—the faultless scenario and five problematic scenarios—are produced as a result of this stage.

Ying-Yi Hong et al (2022) A 3D CNN for PV fault detection and classification is presented in this paper. The Gramian Angular Field (GAF) transform is used for signal pre-processing in the PV system to convert both direct current (DC) and alternating current (AC) data to 3D pictures. When it comes to the overall accuracy (OA) of the testing data, the suggested strategy shows good results. According to simulation results, when used to tackle the relevant problem, the suggested 3D CNN performs better than other machine learning (ML) techniques including k-nearest neighbor, Random Forest, Decision Tree, and Support Vector Machine.

Muhammed Hussain et al (2020) ANN-based photovoltaic (PV) detection algorithm is presented. Only two input parameters were used for the ANN, solar irradiance, and PV output power. Four different ANN-based methodologies were examined and practically testified. Overall, ANN fault detecting accuracy is in the range of 96.5%–98.1%. The validation process provided an overall fault detection accuracy of above 97%. The decrease in accuracy was due to the varying nature of the two systems in terms of total capacity, number of samples and type of faults.

Toubal Maamar et al(2023) The main goal of this project is to use artificial neural networks to detect and locate solar panel problems. As they use learning algorithms to find the best answer to issues, these networks play a key role in the field of artificial intelligence. Before discussing the creation of a multilayer perceptron MLP network for the detection and classification of solar panel problems, the article gives a general introduction of neural networks and their properties. The main issues and future directions for ANN applied to solar panel problems diagnostics are finally listed.

3. METHODOLOGY

3.1 DATASET ACQUISITION

The first phase in the process is dataset acquisition. The aim of this stage is to obtain a set of image data of high- resolution and good clarity. In this research, Solar Panel Images Clean and Faulty Images is used. Solar Panel Images Clean and Faulty Images. The Solar Panel Images dataset is a valuable resource for researchers and developers working on machine learning models for solar panel inspection and maintenance. The dataset can be used to train and evaluate models for detecting different types of damage on solar panels.

3.2 PREPROCESSING

Pre-processing is used for improving the image quality by employing denoising, deblurring, edge enhancement. techniques to handle the imbalance of images in classes.

Fig -1: Dataset image

The provided preprocessing function is designed to prepare image data and labels for a binary classification task, where the goal is to classify images as either "clean" or "faulty." The function takes as input a DataFrame that contains file paths to the images and their corresponding labels. The preprocessing steps involve loading and transforming each image to make it suitable for machine learning. Firstly, the function iterates through the rows of the DataFrame, extracting the image file path and label for each data point. Then, it loads the image, typically resizing it to a uniform size (in this case, 224x224 pixels) and normalizing the pixel values to a range between 0 and 1. This resizing and normalization ensure that all images are represented consistently and have values that are suitable for training a machine learning model. Additionally, the function handles the labels by converting them from their original string form ("clean" or "faulty") into numerical values. It assigns the label "clean" as 0 and the label "faulty" as 1. This transformation is essential for binary classification tasks, where models typically work with numerical labels.
Moreover, the function includes error handling to raise a Value Error if it encounters any label other than "clean" or "faulty," ensuring data integrity. In summary, the preprocessing function transforms raw image data and labels into a format suitable for training machine learning models. It standardizes image sizes, normalizes pixel values, and converts labels to numerical values, all of which are crucial steps in preparing the data for a binary classification

model.

3.3 FEATURE EXTRACTION AND CLASSIFICATION

Feature extraction is the process of converting raw photos into meaningful numerical representations that identify important patterns in image datasets for PV array defect detection. Inorder to achieve our goals of fault classification within photovoltaic (PV) arrays employing artificial neural networks (ANN), a Voting classifier for binary classification, and CNN for multi-class classification, each block or step in the diagram is crucial.

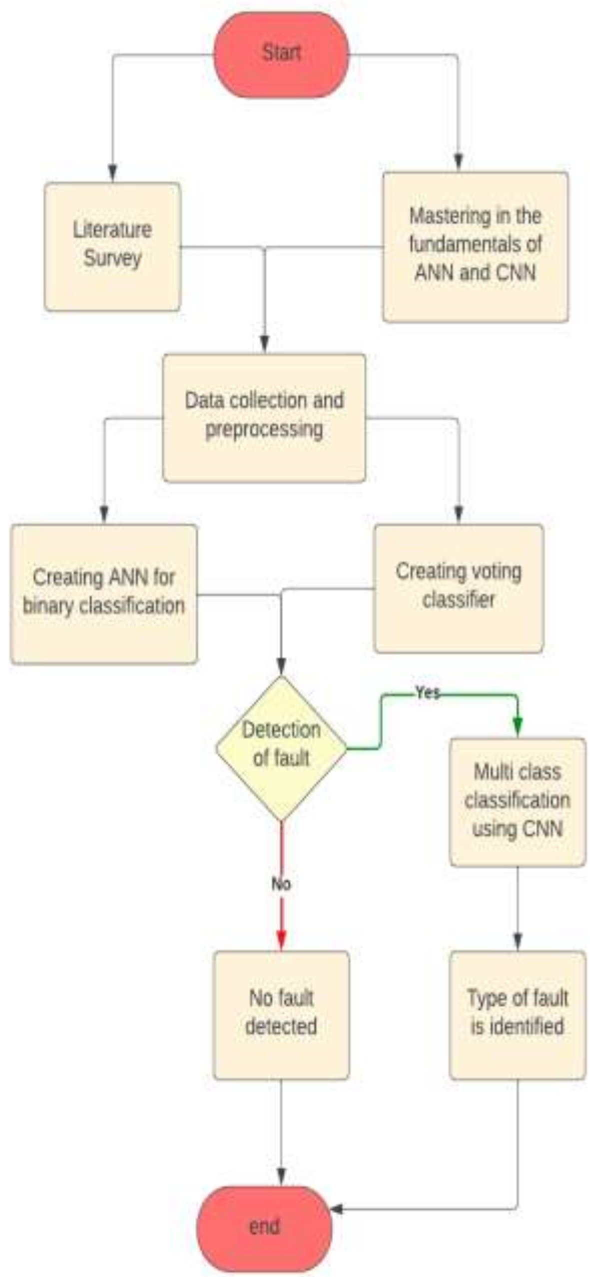

Fig -2: Flow diagram

A stable environment for creating and training ANNs is provided by deep learning frameworks like TensorFlow and Pytorch. TensorFlow and Pytorch, two well-known deep learning frameworks, are used in the research to develop, train, and assess ANN models. Because of their adaptability, scalability, and broad community support, these frameworks are well-known.The effectiveness and dependability of solar energy systems are largely dependent on the correct categorization of defects in PV arrays. This research project describes a structured framework made up of numerous connected work modules to solve this urgent demand. These courses are made to gradually move from comprehension of the body of existing information to the application of cutting-edge machine learning techniques.

Two distinct models are employed: an ANN and a Voting Regressor ensemble for binary classification and CNN for multi-class classification. The ANN is tailored to classify faults as either present or absent, making it a binary classifier. The Voting Classifier ensemble fuses the outputs of two models like decision tress and support vector machine to perform fault detection. Model architecture, loss functions, activation functions, and optimization algorithms are carefully chosen for optimal performance. The input image is resized to 224×224 image. Similar operationsare performed on the image for ANN, voting classifier and CNN.

The objective of the module is to create an ANN architecture specifically for categorizing binary faults. This architecture has been carefully designed to support the intricate nature of PV array data. In order to train the ANN, preprocessed data is used. In this phase, there will be thorough review, which will include evaluations of accuracy, precision, recall, F1-score, and other factors. Iterative fine-tuning is used to improve performance. With the help of the Voting Classifier, an ensemble learning technique, various machine learning algorithms are combined to produce a unified, reliable predictive model. Support Vector Machine: SVM is a potent classifier that identifies the hyperplane that most effectively categorizes a dataset. SVMs are flexible for many types of data since they perform well for both linear and non-linear decision boundaries. Decision Tree: A non-linear model known as a decision tree divides the data into subgroups based on the features. The final prediction is formed at the leaf nodes after a sequence of decisions are reached based on the answers to the questions. Decision trees are useful for some applications because they are simple to perceive and comprehend. To take use of their complementing qualities, SVM and Decision Tree are combined to create a voting classifier. Decision Trees thrive in handling non-linear relationships and producing answers that are easy to understand, whereas SVMs excel at capturing complicated patterns in data. The ensemble may be able to produce more accurate forecasts by mixing several models, particularly when the advantages of one model outweigh the disadvantages of another. This ensemble methodology helps to avoid the dangers of overfitting while simultaneously improving predictive performance. The voting classifier emerges as a formidable ally, ready to deliver accurate and dependable binary classifications across a variety of real-world applications.

The models are subjected to rigorous training using the preprocessed and feature-engineered datasets. This phase entails iterative adjustments to model parameters, with the objective of achieving convergence and optimal performance. Learning rates, batch sizes, and epochs are fine-tuned during this training process. Evaluation of model performance is a pivotal step. In this block, the models are put to the test using relevant metrics such as accuracy, precision, recall, F1-score, and ROC curves. Cross-validation is performed to assess the models' ability to generalize to unseen data. After successful training and evaluation, the fault classification models are deployed in real-world PV array environments. Here, the models operate in real-time, continuously monitoring array conditions.

Any detected faults trigger timely notifications and alerts to operators and maintenance personnel. This synthetic procedure/flow diagram provides a visual representation of our project's methodology for fault classification in PV arrays. Each block or step plays a vital role in advancing our objectives, ensuring the reliability and efficiency of PV array operations, and contributing to sustainable energy generation. The convolutional neural network topologies in the EfficientNet family have been enhanced for accuracy and productivity. The smallest model in the EfficientNet family is EfficientNetB0. It works well for jobs requiring a small amount of computational power, such as those performed on mobile and edge devices, but it may also be applied to a variety of general-purpose picture classification applications. The ability of EfficientNet to strike a balance between accuracy and efficiency is one of its key features. EfficientNet models maintain computational efficiency when compared to larger models (such as ResNet) while offering greater accuracy when compared to smaller models (such as MobileNet).

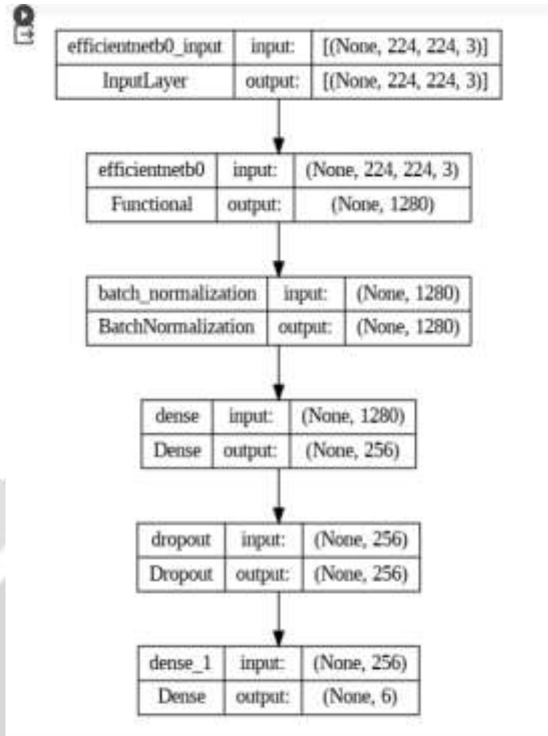

Fig -3: Model Used

With this method, the model performs better on tasks with smaller datasets by utilizing the learned features from the general dataset. Popular deep learning frameworks like TensorFlow and PyTorch allow users to access and use EfficientNet models.

4. CONCLUSIONS

The experiments are implemented on a regular workstation computer with Intel Core i5-8600 CPU, 16 GB RAM, and anNvidia TITAN Xp Graphics Card with 12 GB graphic memory. The software environments are based on Windows 10 OS, and training is carried out on Tensorflow 2.13.0.

Fig -3: Training vs Validation loss

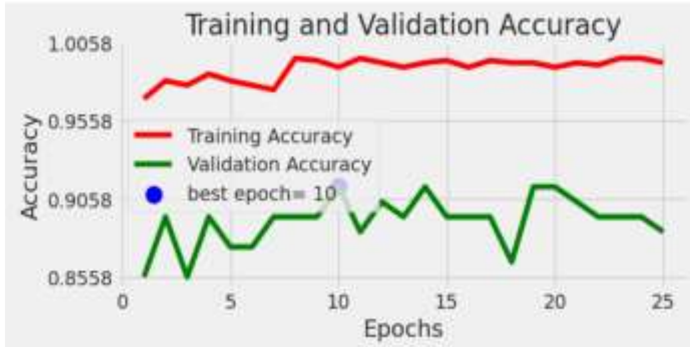

Fig -3: Training vs Validation Accuracy

The proposed methodology for fault classification in photovoltaic (PV) arrays has been successfully implemented, and the results have been impressive, demonstrating the potential for enhancing the effectiveness and dependability of solar energy systems. The significance of reaching 93.5% accuracy for binary classification using Ann and voting classifier combined. And achieved an accuracy of 88.46% for multi-class classification using a convolutional neural network (CNN) are covered in this part, which also delves into the main findings. Over all accuracy of the project leading to 91.82%.

Method	**Models used**	**Number of faults**	**Accuracy**
[1]	Machine learning, CNN	6-classes	74.6%
[2]	Binary classifier- 3 column matrix ,Deep neural network	9-classes	92.95%
[11]	Fault detection- CNN	2-classes	94.30%
[12]	BP-PSO algorithm	2-classes	95%
Proposed model	ANN, Voting classifier, Efficientnet	5-classes	91.82%

Table -1: Performance measure of various analyzed models

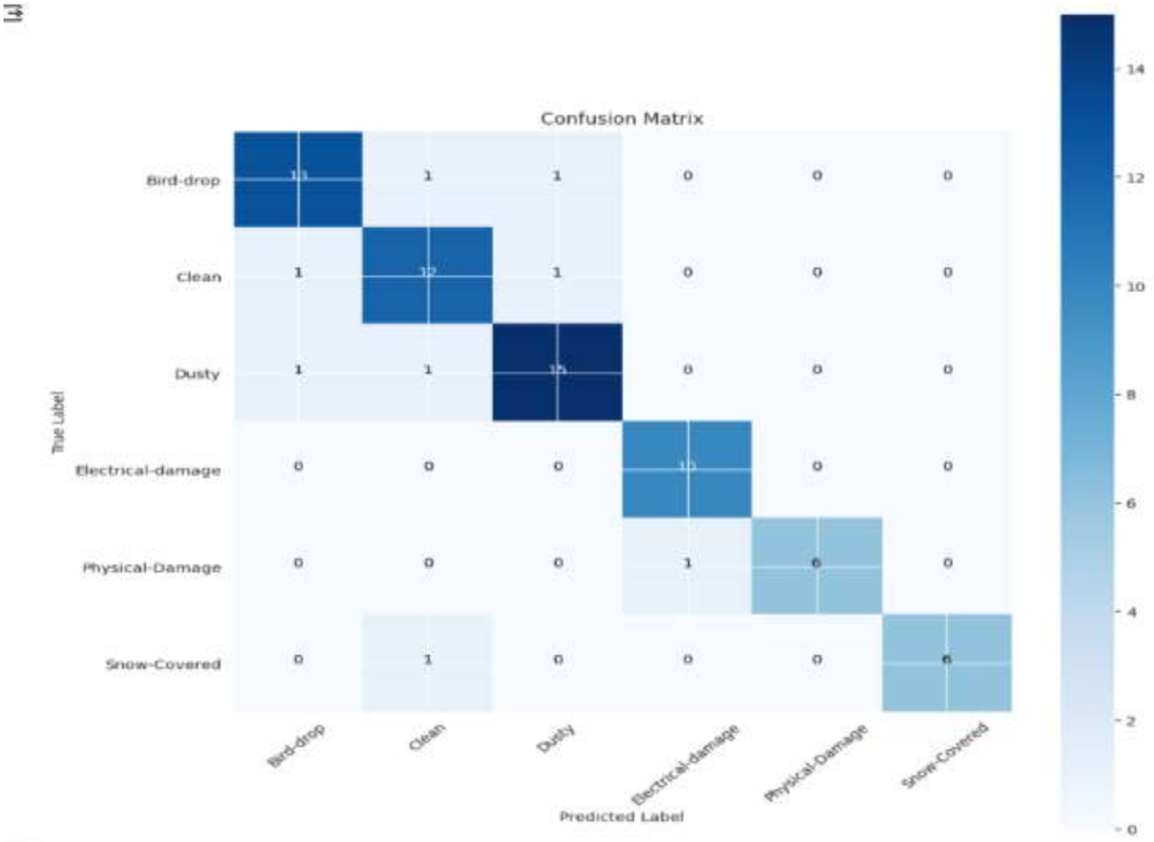

Fig -4: Confusion matrix

The provided confusion matrix offers insights into the performance of a classification model concerning various categories: Bird-drop, Clean, Dusty, Electrical-damage, Physical-Damage, and Snow-Covered. In evaluating its accuracy, the diagonal elements, which represent correct predictions, are particularly notable. For instance, "Clean" items have been correctly predicted 12 times, while "Dusty" items have been accurately identified 15 times. However, there are instances where the model misclassified certain items. For example, "Bird-drop" items have been mistakenly predicted as "Clean", "Dusty", and "Electrical-damage" once each. Another misclassification is the "Physical-Damage" items being incorrectly predicted as "Electrical-damage" once. Such off-diagonal entries are indicative of areas where the model may need improvement. Overall, the matrix serves as a valuable tool to ascertain where the model excels and where it falls short.

Further diving into the matrix, one can observe some specific trends and potential areas of concern. The "Electrical-damage" category, for instance, appears to be a challenging one for the model. It has been correctly classified 10 times, but there have been instances where items from this category were misinterpreted as "Physical-Damage". Such overlaps might hint at similarities between these two categories, at least in the data that the model was trained on. Moreover, it's noteworthy that certain categories like "Snow-Covered" have experienced few misclassifications, with 6 correct predictions and just a single item misclassified as "Clean". This suggests that the model can distinctly identify "Snow-Covered" characteristics from other categories.
On the other hand, the "Bird-drop" category seems to have a more scattered prediction pattern. While it has been correctly classified 10 times, it's also been confused with three other categories. This could be indicative of the varied nature of bird droppings, which can sometimes resemble other forms of dirt or damage, making it a more complex category to predict.

Conclusively, while the model demonstrates proficiency in certain areas, there are evident weaknesses in others. Understanding this matrix can be crucial for refining the model, perhaps through additional training data or tweaking the model parameters, to enhance its overall accuracy and reliability.

Through the creation of fault classification models for PV arrays, this research project has taken on the difficult challenge of enhancing the effectiveness and dependability of solar energy systems. The approach, which includes data gathering, preprocessing, cutting-edge machine learning methods, and real-world testing, has produced notable outcomes and important insights.

This highlights how the ensemble technique is successful at utilising the various advantages of separate classifiers, ultimately producing predictions that are more reliable and precise. This finding is noteworthy because it has significant ramifications for real-time problem detection in functioning PV arrays, which might completely alter maintenance procedures and reduce costs.

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