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Enhanced Detection of Solar Panel Defects Using VGG16-Based Convolutional Neural Networks

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ABSTRACT

Solar energy is a renewable energy source that is expanding rapidly, and it is essential to ensure that solar panel installations are correctly monitored and maintained to ensure that they are operating at their full potential. Detection of various situations and irregularities in solar panel arrays may be accomplished through automated image classification algorithms, which hold great potential. Within the scope of this research, we offer a technique for categorizing images of solar panels that uses the VGG16 convolutional neural network (CNN) architecture. The dataset was taken from Kaggle, which contained 891 Images. The dataset was divided into six categories: Bird drop, Clean, Dusty, electrical damage, physical damage, and snow-covered. In this research, we implemented solar panel image classification using VGG16, a convolutional neural network and achieved a remarkable accuracy of 97.88%. This research exhibited performance compared to the state-of-the-art methods.

Keywords— Solar Panel • Machine Learning • Image Classification• VGG16 • Deep Learning.

I. INTRODUCTION

Solar power, increasingly acknowledged as a viable alternative to fossil fuels, has been playing a crucial part in the settlement of the global energy issue over the last several decades. This is mainly because solar power is safe, reliable, inexhaustible, and kind to the environment. The photovoltaic (PV) technology, designed to convert solar energy into electricity, has made record-breaking advances in conversion efficiencies year after year. On the other hand, local faults are quite common in solar cells because of their naturally granular structure and the specific processes that are used during their production process. These defects significantly reduce the spatial uniformity and overall conversion efficiency of solar cells throughout the manufacturing process [14].

There is an expectation that renewable energy sources, notably solar and wind power, will be responsible for a major share of the world's power generating capacity by the year 2050, accounting for between 75 and 80 percent of the newly installed capacity. The primary reason for this transition toward green energy is the rising demand from the general population as well as the policies implemented by the government with the goals of attaining net-zero carbon emissions, reducing dependency on fossil fuels, and achieving sustainable growth. With the intention of accomplishing these objectives, governments all over the world have made it a priority to develop and put into action steps that will involve investing in large-scale renewable energy power plants. In order to achieve sustainable development, the International Energy Agency (IEA) has selected wind and solar power as two of the most important sources of energy [15].

In [14] a method was proposed for efficiently monitoring and identifying any problems or flaws that may be present in renewable energy assets. The use of drones for image-based monitoring on a regular basis is advised for large-scale renewable power facilities. The photos that are taken are analyzed in order to discover any flaws and to take steps to increase power output. The identification of flaws is made more difficult by the presence of wind turbines that may reach heights of up to 65 meters and solar panels that are spread out over 60 acres of land. As a result, the primary objective is to make use of a computer vision algorithm that is based on deep learning in order to identify impairments in solar photovoltaic panels and wind turbines that are installed on a big scale. Immediately after faults have been found, it is necessary to adopt the proper preventative steps in order to improve the performance of these materials.

II. LITERATURE SURVEY

In this study, we created and implemented a fast, efficient, and simple architecture for an isolated deep convolution-based neural model. The purpose of this model was to accurately categorize PV panels into three groups based on their health status, achieving a 96% accuracy rate. Subsequently, this model was utilized using a transfer learning approach to detect flaws in PV panels. It achieved an impressive accuracy of 97.62% when tested on a new infrared image sample that was not included in the training and validation process. All of this was accomplished within a time frame of eight minutes. In addition, the testing accuracy was increased to 96.36% by utilizing an expanded image dataset that included flaws. The results of the isolated neural network were validated using pre-trained neural networks that have intricate structures, long execution times, and significant storage needs. This methodology can categorize photovoltaic (PV) panels in order to minimize the amount of power lost and provide the lowest repayment period possible [1].

An effective deep learning segmentation architecture was introduced in this paper for the purpose of solar panel detection. Utilizing satellite photographs of solar panels affixed to the ground, buildings, and rooftops, the model was evaluated. The DCSA dataset was employed to generate the ground truth images, for training and testing the datasets, and both. The architecture under consideration was founded upon the Unet and Mobilenet frameworks. By employing depthwise separable convolutions, the proposed model achieved optimal segmentation accuracy while minimizing training time, model parameter count, and floating-point operation demands. In addition to producing precise segmentation maps with precise shapes and boundaries, the proposed model generated fewer incorrect results and false negatives.The aforementioned attributes render the proposed model appropriate for real-time applications and devices with restricted computational capabilities. Subsequent research endeavors may encompass enhancing the model's architecture in order to further refine the outcomes.[2]

In this study, we examine the impact of data augmentation methods on the performance of convolutional neural networks (CNNs) that we propose to classify anomalies in photovoltaic (PV) modules using thermographic images from an unbalanced dataset. The anomalies can be categorized into eleven distinct classes. The high within-class and between-class variance among various categories is investigated using confusion matrices. This can be problematic when developing an automated tool to classify a wide variety of faults in PV plants. The CNN achieved an estimated assessment accuracy of 92.5% in detecting abnormalities in solar energy panels and 78.85% in classifying defects for eight specific classes, as determined by cross-validation [3].

The fault identification in PVM is accomplished through the utilization of aerial images obtained from UAVs and deep learning. In order to extract high-level features from images that are classified utilizing the softmax activation function, convolutional neural networks (CNN) are implemented.

The process of defect classification and feature extraction is executed through the utilization of a pre-trained VGG16 network. In the investigation, all of six conditions for testing are considered. Considered test conditions include burn marks, delamination, discoloration, glass breakage, excellent panels, and snail trails. The performance of the have been trained CNN model is assessed and its classification outcome is displayed [4].

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This paper examines five key aspects: the diverse array of faults that may arise in photovoltaic (PV) panels, the advantages of identifying faults in PV panels, the utilization of artificial intelligence (AI) techniques for fault diagnosis in PV panels, and the online/remote monitoring of PV panels.[6]

The purpose of this study is to identify photovoltaic solar power plants in Brazil through the use of mosaicking and semantic segmentation to classify large images. Four backbones were compared to four architectures (Feature Pyramid Network, U-net, DeepLabv3+, and Pyramid Scene Parsing Network): Efficient-net-b0, Efficient-net-b7, ResNet-50, and ResNet-101. In the process of mosaicking, an overlapping-pixel sliding window was assessed with varying stride values (8, 16, 32, 64, 128, and 256). Our findings indicate that the models yielded comparable results, suggesting that in many scenarios, acquiring high-quality labels is a more suitable approach than relying on models. U-net demonstrated marginally better metrics, with the Efficient-net-b7 encoder constituting the optimal configuration (98% accuracy in general, 91% IoU, and 95% F-score). Mosaicking progressively improves outcomes (specifically, the receiver's operating characteristic area under the curve and precision-recall) as the strid decreases.[7]

Within the realm of image analysis, the cumulative distribution function (CDF) and the picture histogram are both extremely important components. The utilization of techniques such as grayscale conversion, adaptive histogram equalization, and histogram equalization is employed in order to make the process of analyzing thermal pictures of solar panels more straightforward. These procedures, according to the findings of the experiments, result in an improvement in the histogram and CDF properties of the thermal pictures that have been processed. In addition, the convolutional neural networks (CNNs) that were utilized in the suggested method were able to obtain a classification accuracy of 97% on the augmented pictures [8].

It is possible to figure out the sun's power output using sky-facing cameras and machine learning techniques, according to one study. The utilization of this ground-based methodology offers a cost-effective means of comprehending solar irradiance and approximating output from photovoltaic solar plants.[9]

This article presents a significant synopsis of the present state of research concerning dust detection methods for photovoltaic panels and identifies promising prospects for future advancements in this domain [10].

The findings indicate that the accumulated density function serves as a practical method for assessing the condition of solar panels. It could potentially offer maintenance staff a framework for determining whether solar cell replacement is required, thereby simplifying the maintenance process and enhancing overall power generation efficiency. Notably, image recognition can improve the visibility of infrared (IR) images, and the cumulative chart can be used to determine the cell's defect rate. The integration of these two techniques yielded an immediate, precise, and rapid defect assessment [11].

The purpose of this study is to provide a novel technique to object identification with the intention of developing a surface tracking system that is both cost-effective and efficient for energy consumption assets. On a regular basis, high-resolution photos of the assets are acquired and processed in order to identify any surface or structural defects that may have occurred on solar panels and wind turbine blades. For the purpose of surface defect classification, we suggest the utilization of the Vision Transformer (ViT), which is a contemporary attention-based deep learning model implemented in the field of computer vision. When compared to other deep learning models, such as MobileNet, VGG16, Xception, EfficientNetB7, and ResNet50, the ViT model proves to be superior in terms of performance. It achieves accuracy scores that are greater than 97% for assets in wind and solar energy plants [12].

There are four alternative criteria that are proposed in order to characterize the contours of mask images. These criteria include the contour region, the perimeter, the aspect ratio, and the ratio of the contour area to the area of the bounding rectangle used for the contour. Using these determined criteria, three different types of classifiers, namely the Support Vector Machine (SVM), the K-Nearest Neighbors (KNN) method, and the Decision Tree, are subsequently utilized in order to identify a variety of PV panel defects. Using a Decision Tree in conjunction with a U-Net neural network that has been properly trained, it is possible to discover flaws in photovoltaic panels with an accuracy of 99.8 percent, according to research findings [13].

III.METHODOLOGY

Many algorithms are used for image classification of solar panels, but we have implemented the VGG16 model in this research.

3.1 Dataset Description

Dust, snow, bird droppings, and other particles can accumulate on the surface of solar panels, affecting the efficiency of the solar modules and, therefore, the quantity of energy they produce. Monitoring and cleaning solar panels is essential; hence, developing an ideal technique to monitor and clean these panels is necessary to maximize the modules' efficiency, decrease maintenance costs, and minimize the resources used. This dataset aims to assess the capability of several machine learning classifiers to detect dust, snow, bird drops, physical defects, and electrical faults on the surfaces of solar panels with the maximum possible degree of accuracy.

Each of the six class folders contained within this directory can be classified. Considering that the photographs were obtained via scraping them from the internet, there is a slight disparity in the total number of images acquired.

- Clean: This category contains images of solar panels that have been cleaned.
- Dust: This section contains images of solar panels covered with dust.
- Bird drop: Images of bird-drop on solar panels may be found in this compilation of directory entries.
- Electrical damage: This section contains images of solar panels damaged by electricity.
- Damage to the body: This category contains images of solar panels that have suffered physical damage.
- Snow Covered: You can find images of solar panels with snow covering them in this area.

3.2 VGG16 Model

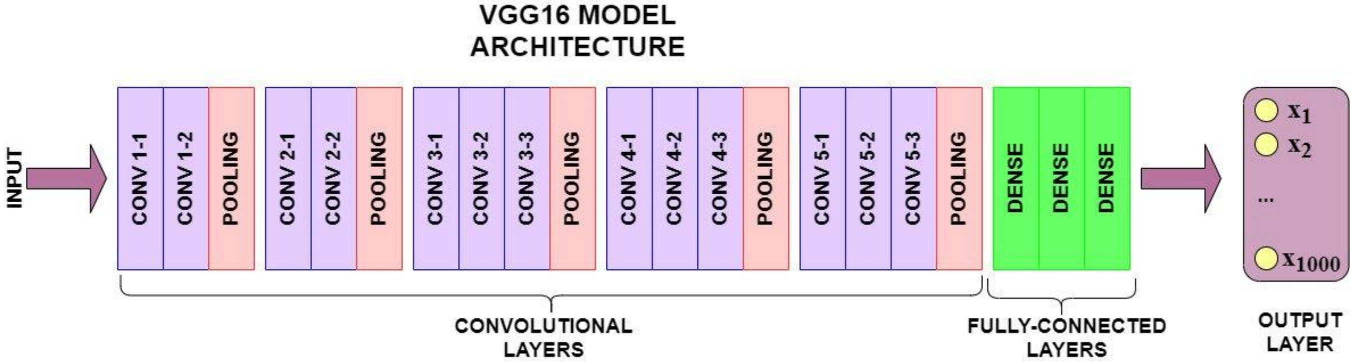

Fig 1. VGG16 Model Architecture Image Source Adapted from []

The convolutional neural network (CNN) known as VGG16 is now widely used for image categorization. A group at the University of Oxford known as the Visual Geometry Group (VGG) was the one that initially presented it in 2014. It has been demonstrated that the deep neural network known as VGG16, which consists of sixteen layers, is particularly successful in image categorization. Concerning a variety of benchmark datasets, notably ImageNet, it has produced results considered to be state-of-the-art.

The following are some of the causes why VGG16 is a preferred choice for image classification:

- The VGG16 algorithm is used for various image classification applications, including detecting objects, categorizing images, and identifying individuals.
- Accurate: It has been demonstrated that VGG16 is entirely precise in image classification, obtaining results considered to be state-of-the-art on various benchmark datasets.
- Because of its relatively high efficiency, VGG16 is an excellent option for real-time applications.

IV. RESULTS & ANALYSIS

In this research, we implemented solar panel image classification using the VGG16 algorithm, a convolutional neural network (CNN) typically used for image classification. The main contribution of the research is to assess the ability of various machine learning classifiers to detect dust, snow, bird drops, and physical and electrical on solar panel surfaces with the highest possible accuracy.

There are some reasons why we use the VGG-16 algorithm.

- Accuracy: It has been demonstrated that VGG16 is entirely accurate in image classification, obtaining results considered to be state-of-the-art on various benchmark datasets. In the case of the ImageNet dataset, for instance, the VGG16 algorithm gets an accuracy of 92.7%.

- Transfer learning is a technique that enables us to utilize a pre-trained model to improve the performance of a new model. VGG16 may be used for transfer learning, which includes implementing transfer learning. Transfer learning is frequently utilized when we only have a tiny dataset for our new model.
- Because of its user-friendliness, VGG16 is included in various deep learning frameworks, including Keras and TensorFlow. Because of this, it is simple to employ for tasks involving image categorization.

The dataset used is Solar Panel Images Clean and Faulty Images taken from Kaggle. It contains 891 images, categorized as Bird-drop, Clean, Dusty, electrical damage, physical damage, and snow-covered.

Dust, snow, bird droppings, and other particles can accumulate on the surface of solar panels, affecting the efficiency of the solar modules and, therefore, the quantity of energy they produce. Monitoring and cleaning solar panels is essential; hence, developing an ideal technique to monitor and clean these panels is necessary to maximize the modules' efficiency, decrease maintenance costs, and minimize the resources used.

Fig shows the graph for training data accuracy and loss.

Fig 2. Training Data Accuracy & Loss

Fig shows the graph for training and validation accuracy.

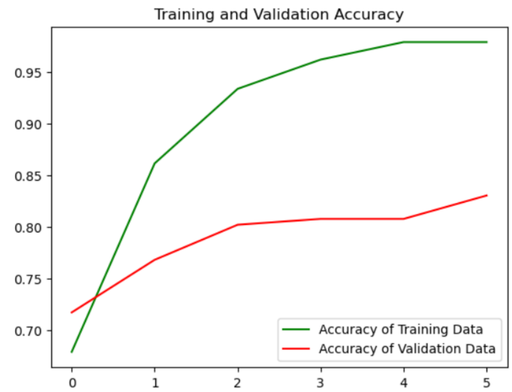

Fig 3. Training & Validation Accuracy

Fig shows the graph for training and validation loss.

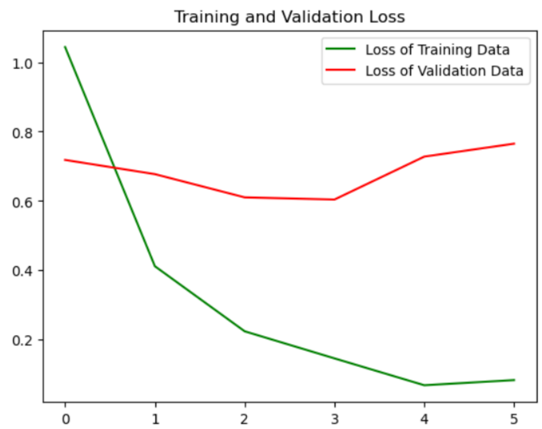

Fig 4. Training & Validation Loss

Fig shows the detection of bird drops, dust, and physical damage to solar panels.

Fig 4. Image of Solar Panel Classification

V. EXISTING RESEARCHES IN SOLAR PANEL IMAGE CLASSIFICATION

Current research in solar panel image classification employs advanced techniques involving drones and machine learning. One approach involves using drones to capture both RGB and thermal images of solar panels. For panel identification, a Convolutional Neural Network (CNN) based on YOLOv5 is utilized, while an EfficientNet classifier is used for anomaly classification. This classifier categorizes issues into several types, including cell, multi-cell, diode, and multi-diode problems [15].

Research has also examined ensemble techniques utilizing logistic regression, support vector machines, and artificial neural networks for quality evaluation based on infrared images. These methods have demonstrated over 90% accuracy in damage assessment [16].

VI. CONCLUSION

In this paper we have implemented solar panel image classification using VGG16 algorithm which is a convolutional neural network and achieved an remarkable accuracy of 97.88% and this research has also exhibited state of the art research methods. The results of the experiments reveal that the proposed approach succeeds as it achieves a high level of accuracy when discriminating between multiple types of solar panels. The results of our research indicate that the utilization of deep learning approaches, such as VGG16, has the potential to make a substantial contribution to the automated monitoring and maintenance of solar energy systems, hence aiding the general adoption and sustainability of these systems.

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