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ORIGINAL RESEARCH ARTICLE

Solar Panel Damage Detection and Localization of Thermal Images

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Abstract Solar panels have grown in popularity as a source of renewable energy, but their efficiency is hampered by surface damage or defects. Manual visual inspection of solar panels is the traditional method of inspection, which can be time-consuming and costly. This study proposes a method for detecting and localizing solar panel damage using thermal images. The proposed method employs image processing techniques to detect and localize hotspots on the surface of a solar panel, which can indicate damage or defects. The findings of this study show that the proposed method is effective in detecting and localizing solar panel damage and can reduce inspection time and cost. This study proposes a method for detecting and localizing solar panel damage using thermal images. The proposed method employs image processing techniques to detect and localize hotspots on the surface of a solar panel, which can indicate damage or defects. The findings of this study show that the proposed method is effective in detecting and localizing solar panel damage and can reduce inspection time and cost. The proposed method has the potential to improve the efficiency and lifespan of solar panels while also contributing to the wider adoption of renewable energy. This research suggests a way for detecting and localizing solar panel damage using thermal imaging, which could get rid of the requirement for manual visual examination. The suggested technology detects and localizes hotspots on the surface of solar panels, which indicate faults or damage. This method can increase the efficiency and longevity of solar panels, hence promoting the use of renewable energy. Future improvements, such as incorporating AI and ML algorithms and advances in thermal imaging technologies, could improve the accuracy of this method even further.

Keywords Solar panel · Damage · Detection · Surface · Energy · Localization · Thermal images · Model · Deep learning

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Introduction

Solar power is a significantly important increasing renewable energy source, and solar panels are an essential part of solar energy systems. Yet, several operational and environmental conditions can damage solar panels and lower their performance. To maintain effective operation and maintenance of solar power facilities, prompt diagnosis and localization of solar panel damage are essential. A popular non-destructive testing method for spotting damage to solar panels is thermal imaging. To assess thermal photographs of solar panels and pinpoint regions of damage, machine learning algorithms have been created. Unfortunately, the accuracy and effectiveness of current methods are constrained.

In this study, we present a more effective technique for locating and identifying solar panel damage using thermal imaging. Our approach uses a deep learning algorithm that was created using a significant collection of thermal images of solar panels. We have used transfer learning strategies to improve the model's accuracy while using less training data. We further demonstrate the efficiency of our system in quickly and precisely identifying solar panel damage by applying it to a large dataset of thermal images of solar panels.

Overall, our research makes an important contribution to the field of solar panel damage detection and localization, and it demonstrates how deep learning techniques have the potential to improve the accuracy and effectiveness of this crucial task.

Literature Survey

A new method of damage identification was employed by Shihavuddin et al. [1] to assess the health of solar and wind systems using drone imagery. In this field, the effectiveness of object detection algorithms has been compared. It has been shown that a trained model combining infrared and drone data is very accurate. A collection of annotated solar and wind system damages has also been created for research purposes. Overall, this approach seems like a possible option for improving maintenance while raising the effectiveness of energy generation.

Selvaraj et al. [2] compared three different models: AlexNet, GoogleNet, and SqueezeNet to use deep learning techniques to find flaws in solar panels. With a testing accuracy of 99.815%, the SqueezeNet model performed the best. Then, the researchers trained the SqueezeNet model on thermal images of solar panels, achieving a testing accuracy of 99.74% and an F1 score of 0.9818. The solar industry might gain greatly from this strategy.

In their paper, Prabhakaran et al. [3] state that a unique method known as RMVDM, HOLT was created to discover, classify, and diagnose flaws in PV images. RHA preprocessing is employed to improve the quality of the images, while GSQA is utilized to extract features. With the help of these features, the network is trained to compute the SDCS, EDCS, CDCS, and DDCS measures, which are used to identify and locate mistakes. The suggested method has a 97.6% accuracy rate for defect detection. In the future, the method can be improved by integrating time-variant photos of solar panels to achieve even more efficiency.

In this research, Li et al. [4] introduce YOLO-FIRI, a brand-new one-stage object detector for infrared images. It is also recommended to use YOLO-FIRI, a better version with improved detection precision for small objects. The recommended models combine shallow and attention features to recognize objects with poor resolution and ambiguous attributes. The models perform at the forefront on the KAIST and FLIR datasets. Future research on the use of infrared video for object detection would be intriguing because video sequences exhibit a strong relationship between frames and could perhaps improve detection performance.

To ensure peak performance, Kirubakaran et al. [5] stated that massive solar power installations need to be monitored. It is challenging to find defects in specific solar panels or strings. A common type of fault is hot spots brought on by higher internal resistance. To find heated hotspots, researchers used a variety of image processing algorithms with MATLAB. They could quickly locate hot areas by using thermal photography and the Hough transform method. The researchers found that hot spots were more frequent in the older panels due to higher internal resistance after running the same code on both the old and new panels. The results revealed a strong correlation coefficient and experimental testing verified that older panels performed better.

Studies by Chaudhary et al. [6] explore the potential for optical inspection, infrared thermography, and MATLAB image processing to identify different solar panel problems. The study evaluates how airborne contaminants such dust, tree leaves, bird droppings, cement deposits, and grime affect solar panels' surfaces. To locate hotspots and bubbles and analyze the consequences of these depositions and environmental factors on the health of solar panels, the researchers used thermal image processing. The results are shown in tables, bar charts, and temperature graphs in three dimensions, demonstrating how these conditions might reduce the production efficiency of solar panels.

According to Henry et al. [7] research, a novel drone-based infrared thermography system can automatically find and locate broken PV modules in a PV power plant. The drone system's twin camera setup consists of a thermal camera and an RGB camera. The drone can fly autonomously without requiring manual control thanks to our automatic flight route planning system. Additionally, the system can recognize and precisely localize damaged PV modules. Unlike previous methods, we tested our approach in a real 1-MW power plant in Suncheon, South Korea. The results demonstrate that our method can accurately and independently pinpoint faulty modules.

According to Dáz et al. [8], recognizing solar panels may be challenging because of different backgrounds, power lines that run parallel to the panel edges, and weed shadows on the panel edges. Nevertheless, two-panel detection technologies have been created that can accurately identify solar panels in such circumstances. While the second method makes use of deep learning, the first methodology uses support vector machines for image rectification, segmentation, and classification of picture segments. A post-processing phase is used in both strategies to improve panel detection. When evaluated on 100 thermal pictures from 11 drone flights at three solar projects, both approaches achieved excellent accuracy metrics. In future work, lens distortions will be lessened, other panel projection techniques will be tested, geographic information will be added, and panel identification and panel failure algorithms will be combined.

According to Hwang et al. [9], a problem detection system for the solar panels of solar-powered street lighting employs multilayer neural networks (MNN) and adaptive resonance theory 2 neural networks (ART2 NN). We feed the two neural networks the open-circuit voltage relative to duty cycle to identify a problem in a solar panel. As a result, we can utilize them to confirm the solar panel defect diagnosis. We also provide a graphical user interface for the suggested system for diagnosing solar panel faults. The problem diagnosis system we provide might be used in related systems and gadgets.

A new defect detection technique for photovoltaic systems is presented in the Vieira et al. [10] study. Combining two machine learning algorithms, the method locates short-circuited modules and unconnected strings on photovoltaic systems. The first algorithm employs a multilayer feed-forward neural network and takes as inputs irradiance, ambient temperature, and power at the maximum power point. The Sugeno-type fuzzy logic system receives the neural network output and uses it to count the number of defective modules in the power plant. A simulated dataset was used to train the suggested approach, and experimental data was used to validate it. Detecting disconnected strings with 99.43% accuracy and short-circuiting photovoltaic modules with 99.28% accuracy, respectively, were the outcomes.

Solar energy has shown enormous increase, according to Hazem et al. [11]. Photovoltaic (PV) systems are in extremely high demand and have been widely incorporated into all facets of contemporary life. This dramatic increase prompted the development of intelligent technology to identify and categorize various problem kinds in PV models. Electroluminescence (EL) imaging techniques have drawn more and more attention, particularly when convolutional neural networks (CNNs) are used for EL fault detection and classification. This study develops a multi-scale CNN model-based technique for defect identification and categorization of EL pictures from PV cells. Two approaches were used; the first uses two chosen DNNs (SqueezeNet and MobileNet-v2) in a development-based transfer learning technique, while the second relies on creating a light-depth CNN (referred to as HazELNet). The public ELPV dataset was used for the tests, which were run using 4-class and 8-class scenarios, after adequate data augmentation. When using the 8-class technique, experimental findings have demonstrated promising performance in terms of the acquired validation and testing accuracies (92.4–97.1% and 87.7–89.0%, respectively). In addition, when compared to SqueezeNet and MobileNet-v2, the suggested HazELNet has improved classification performance while showing a superior reduction in computational cost.

According to Pa, Mary et al. [12], solar energy is a dependable and trustworthy renewable energy source. However, flaws and irregularities can occur in photovoltaic systems, reducing their effectiveness and raising maintenance expenses. Convolutional neural networks (CNNs) and adaptive neuro-fuzzy inference systems (ANFIS) are two examples of artificial intelligence (AI) methodologies that researchers have used to create clever mechanisms to address this issue. Using photos or signals gathered from the solar panels, these models may identify and categorize defects in the panels. It is discovered that the ANFIS-based defect detection technique is reliable and simple, increasing the reliability of PV systems while reducing energy consumption and maintenance expenses. ANFIS models can also be used to quickly and accurately forecast power generation in combined cycle power plants. These AI-based models are generally effective tools for enhancing renewable energy systems.

Several artificial intelligence techniques are used by Ghoneim et al. [13] to identify and estimate electrical faults in photovoltaic (PV) farms. Out of a total of 12 strategies, the fault detection approaches of random forest, logistic regression, naive Bayes, AdaBoost, and CN2 rule induction were chosen because they yielded better fault detection decisions. Measurements of plant voltage, current, and power, as well as distributed PV current, were used to develop the suggested methodologies. The treatment of temperature, radiation, and fault resistance was random. The Orange platform was used to develop the proposed categorization model. A classification tree with seven nodes, four leaves, four levels of depth, and relative edge width to parents was seen. Four of the key fault feature properties, totaling 30, allowed fault identification using the chosen algorithms. We considered the many fault types that can occur in a PV farm, such as string fault, string-to-ground fault, and string-to-string fault. The performance of the chosen classifiers was assessed and contrasted in relation to the crucial decision-making criteria of precision, recall, classification accuracy, F-measure, specificity, and area under the receiver-operating curve. A 250-kW PV farm that is connected to the grid was constructed using Simulink/MATLAB, including converter control. Results showed that AdaBoost performed at its peak.

A method based on artificial intelligence is created by Gao et al. [14] to identify various PV array defect types. This approach incorporates the potent multilayer perceptron (MLP) and one-dimensional convolutional neural network (1-D CNN) deep neural networks. A PV system that can simulate typical line-line, line-ground, and open-circuit faults is first modeled using Matlab/Simulink, and a lot of normal and fault data are simulated to verify and validate the suggested method. Then, large amounts of simulation data are input into MLP and 1-D CNN to learn the traits of various fault kinds, to identify and separate such errors. Finally, the outcomes demonstrated the neural network-based PV array fault detection technique's high accuracy and efficacy.

According to Narmadha et al. [15], solar power plants should be examined for ideal power yield. This restores efficient power generation from power plants while identifying malfunctioning photovoltaic (PV) systems, associations, and accumulations of dust on solar panels that are producing less electricity. Some of the problems are also carried out. An automated IOT-based framework for checking solar power is suggested in this article because it is thought that solar power is updated via the internet. The sensors used in this proposed work are the Light-Dependent Resistor (LDR), Current Transformer (CT), and Potential Transformer (PT) sensors, each of which is integrated into an Arduino-based framework. These sensors are employed in the estimation of solar panel screening borders. The solar power is assessed in this work utilizing a parameter of LDR sensor power and panel estimated voltage. This study presents the artificial neural network (ANN), a machine learning approach used to precisely detect and rank defects. As a result, the framework continuously detects the PV, and the IOT framework monitors the power yield online. The IOT connection uses a successful GUI to show the client these boundaries and warns them when the yield goes below predetermined cutoff points. This ensures the best power yield and makes remotely monitoring solar systems incredibly simple.

According to Li et al. [16], photovoltaic (PV) modules' current-voltage characteristics (I–V curves) reveal a lot about their condition. Only a portion of the information from the I–V curves is used for diagnosis in the literature. In this work, a method is created to fully utilize I–V curves for diagnosing PV faults. In the pre-processing step, the I–V curve is first corrected and resampled. Then, using the current vector that has been resampled directly, or after transforming it using a Gramian angular difference field or recurrence plot. For the categorization of the eight conditions (healthy and seven faulty conditions) of the PV array, six machine learning techniques—artificial neural network, support vector machine, decision tree, random forest, k-nearest neighbors, and naïve Bayesian classifier—are tested. The optimal performance (accuracy and processing time) for each classifier while using various input features is carefully investigated. Additionally, it addresses robustness to environmental noise and measurement mistakes. With both simulation and real-world data, it is discovered that the best classifier achieves 100% classification accuracy. Analysis is also done on feature dimension reduction, classifier robustness to disturbance, and the effect of transformation.

Technology Stack

The solar panels use Python's image processing, machine learning, and deep learning capabilities to detect damage. Popular modeling libraries for solar panel damage detection include OpenCV, TensorFlow, Keras, and PyTorch. The TensorFlow GPU module is used to accelerate deep learning model training by exploiting the parallel and optimized properties of GPUs. Image processing including infrared image analysis using libraries such as OpenCV is important in the preparation and analysis of solar panel images for damage detection. The KNN and YOLO algorithms are used for machine learning tasks, where KNN is based on the visual similarity in accuracy and efficiency of track degradation detection and is improved. Python libraries with image processing, machine learning, and deep learning capabilities, such as OpenCV, TensorFlow, Keras, PyTorch, and Scikit-learn, are widely used CNNs, and YOLO is the deep learning algorithm presented and classify damaged objects, with or without CNNs classified objects are analyzed and YOLO excels in object recognition accuracy transfer learning is also used to prepare pre-trained models for work the uniqueness of seeing the depletion of solar energy. Deep learning increases detection accuracy while reducing the need for manual testing.

Proposed System

Figure 1 shows the proposed model, which will be superior to the current model. New layers will be added to make the current model more accurate. Feature extraction will be used to improve the parameters. Data enhancement can be used to expand the dataset so that it can be trained on a larger scale. Current models use infrared images instead of thermal maps, while thermal maps will make it easier to identify damaged areas in the new model. The primary purpose of SPPF rather than the SPP level is to improve the processing of changes in focus or configuration Furthermore, the focus level of the YOLO-FIRI system has been significantly improved replaced by a 6 × 6 convolutional layer, and timed works faster than its predecessor's results. To further enhance the performance of the model, a separate Channel-wise Attention component is added to the output tensor. This product has the potential to produce results that far exceed expectations.

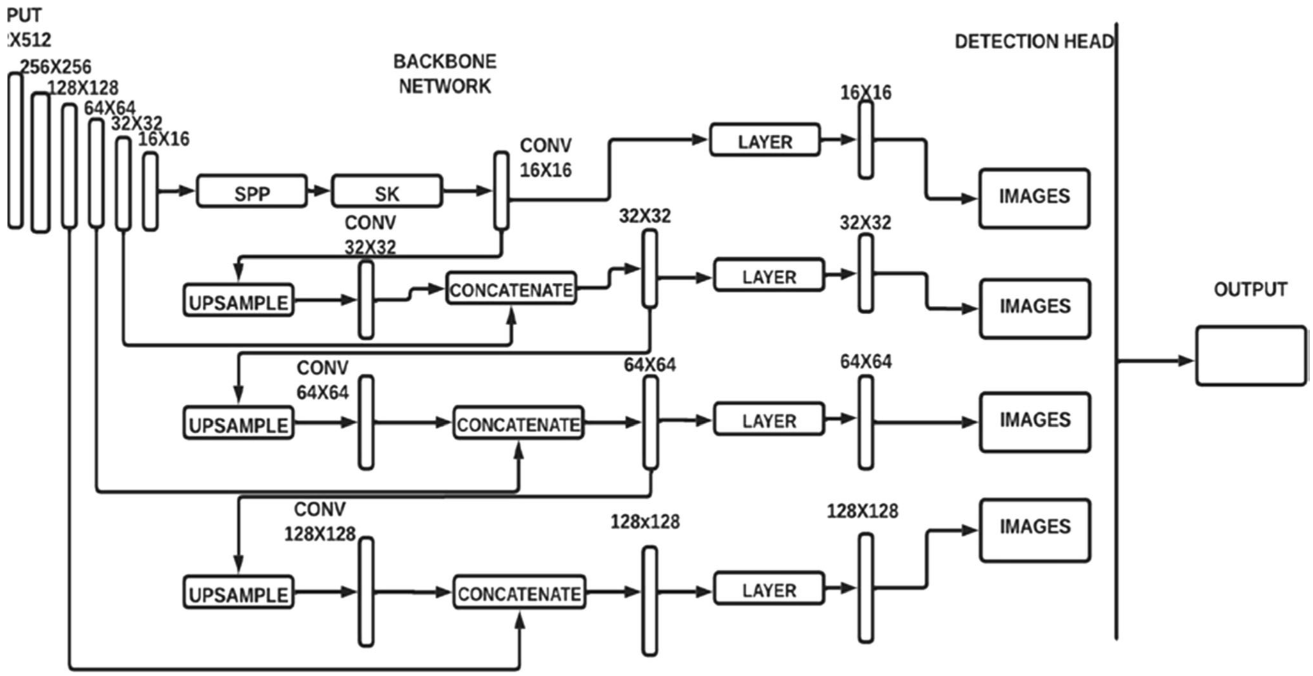
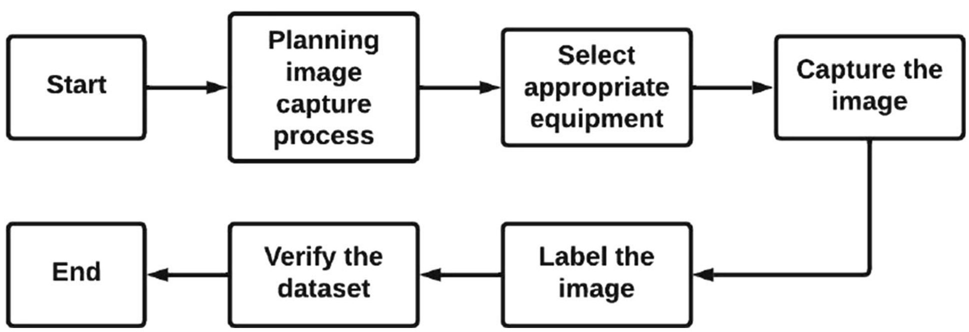


Fig. 1 Proposed system

Fig. 2 Data collection



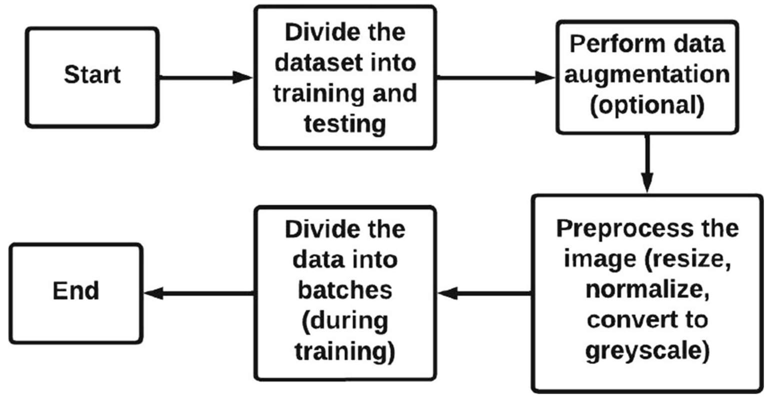
Methodology

To set up an image recording system to collect a set of 300 images divided into two types of defects in solar panels, choose the appropriate equipment, record with a preset image recording system, stop exist for labeled images based on their deficiencies, and verify the dataset to ensure that it meets the required requirements. This can be done by determining the imperfections to be captured, choosing the right thermal camera, taking a continuous photo, manually annotating images, or using image stamping software, and checking the balance of data sets, accuracy of characters, and image quality to ensure correctness. Figure 2 shows the data collection methodology.

Figure 3 shows the methods used to construct the dataset. To prepare it for use in machine learning models, the data set must be separated into training and test sets and each image must be labeled according to the type of error it represents. Typically, the training set is 85% of the data set, while the test set is 15%. Techniques such as random rotation, flipping, and cropping can be used to intentionally increase the size of the data set and improve the performance of the model. Preliminary processing of images by shrinking, normalizing, and converting to grayscale or any other acceptable format is also necessary before training the model. Finally, in training, data are often partitioned into fixed-size groups to increase performance and reduce memory requirements.

The project "Solar Panel Damage Detection and Localization of Thermal Images" aims to use object recognition algorithms to detect and classify damage in regular thermal shots of solar panels (Fig. 4 shows localization well). Two sets of data are collected and recorded description, two object recognition models are trained, using a well-known framework New images are used, and post-processed to eliminate false positives and increase

Fig. 3 Data preparation



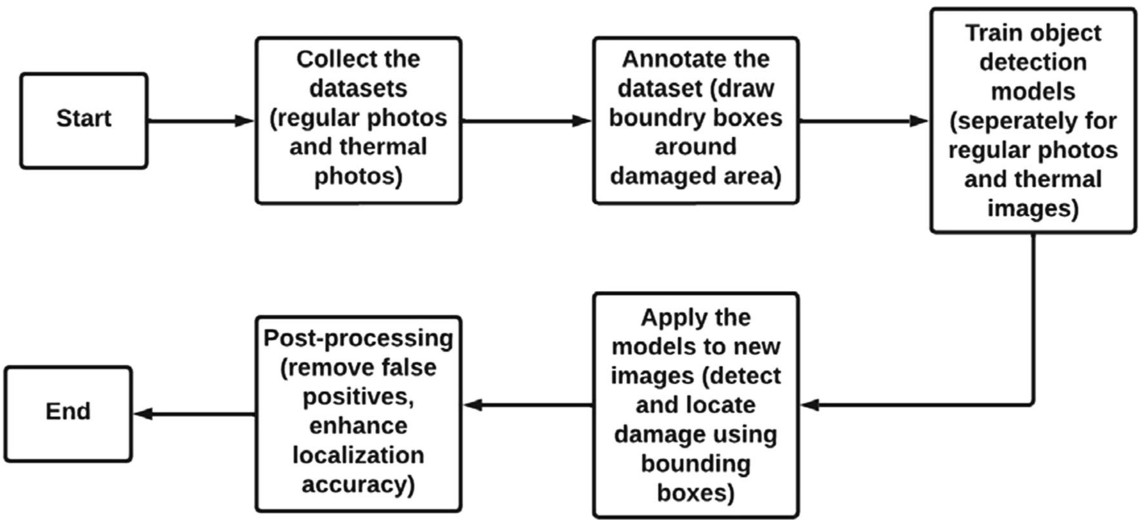


Fig. 4 Localization

local accuracy Advantages of local applications for solar equipment damage detection include faster detection, greater accuracy, lower cost, safety, and increased efficiency, shortening the time and effort required for repair

The article discusses data enhancement techniques that can be used in the project "Solar Panel Damage Detection and Localization of Thermal Images" to improve the accuracy of machine learning models and reduce overfitting cropping, flipping, brightness and contrast tweak, random cropping, and Gaussian noise are among the available options. These techniques can increase the richness and diversity of the dataset, as well as train the model to detect damage under different temperature, illumination, and viewing conditions. Figure 5 shows the data enhancement process.

The importance of feature extraction in modeling solar panel damage localization and detection using thermal images is discussed in the text. It includes important considerations when extracting features, e.g., selection of deep neural networks, using trained models, attentional mechanisms, hyperparameters, data enhancement, routine methods. Figure 6 emphasizes that model accuracy and efficiency can be improved by carefully applying the feature extraction technique.

The inclusion of a fourth layer improves the deep neural network's ability to detect and localize solar panel degradation using thermal pictures, as illustrated in Fig. 7. It enables the model to capture more complex properties and recognize subtle damage patterns. To avoid overfitting, accelerate training, and improve model performance, procedures such as regularization, transfer learning, and hyperparameter tuning can be applied. These factors must be considered carefully when deciding whether to add a fourth layer to the network.

Adding heatmap images to the detection system improves the accuracy of solar damage detection, and thermal imaging is applied to location heatmaps to obtain a simulation of the solar panel surface temperature distribution accuracy, making it easier to identify and diagnose problems. Pre-processing techniques can improve the quality of the thermal image for better localization and detection. Figure 8 shows the method of detection by heat

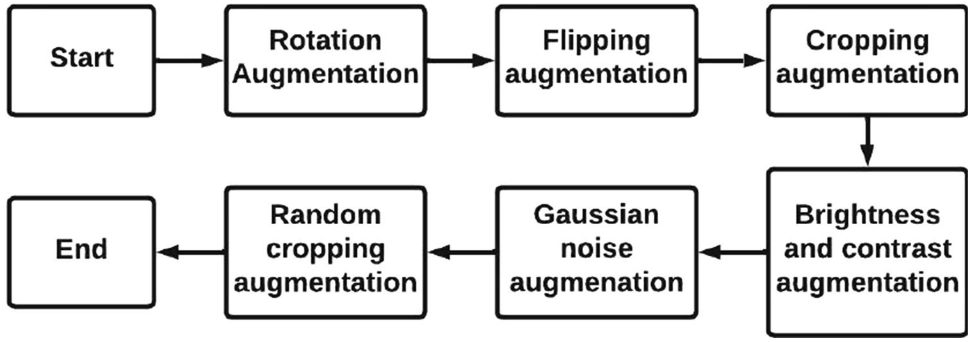


Fig. 5 Data augmentation

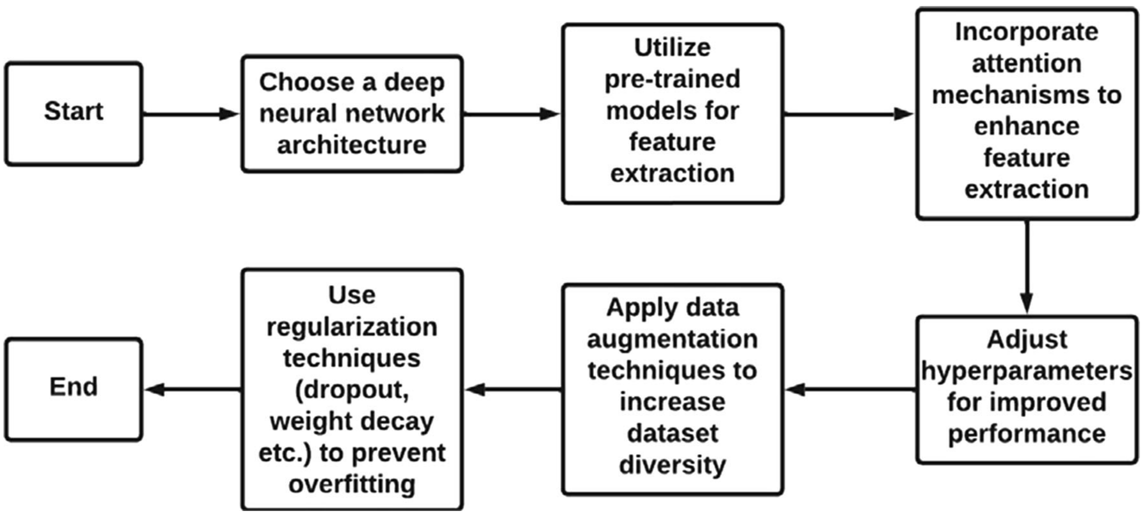


Fig. 6 Feature extraction

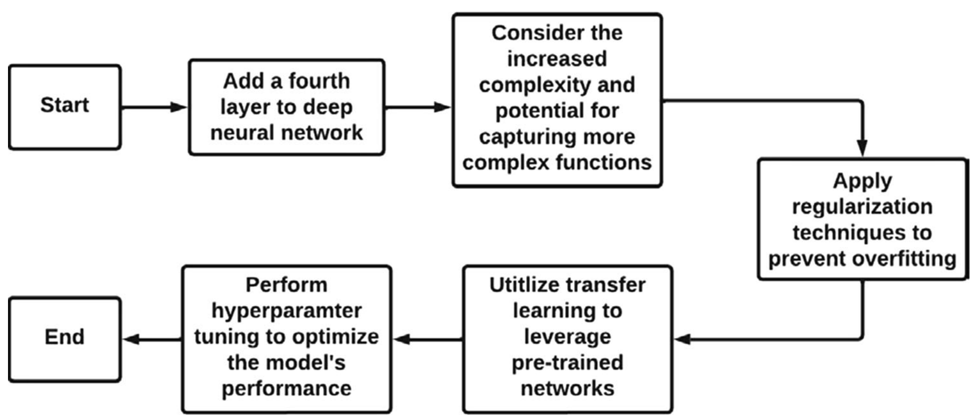


Fig. 7 Model improvement

map diagram. Heat maps can improve system efficiency, reduce maintenance costs, and provide decision-makers with a visual representation of the extent of damage.

When training a deep neural network for solar panel damage detection and localization using thermal images, there are numerous crucial elements to consider. To learn a wide range of characteristics and improve generalization, the model should be trained on a diverse and up-to-date dataset. Using a GPU for training can substantially expedite the process due to its capabilities for parallel computation. It is critical to develop a suitable loss function that maximizes both localization and detection accuracy. Hyperparameters like learning rate, layer count, and batch size should be changed to improve the model's performance. For efficient analysis, the data set should be divided into training, validation, and test sets. Evaluation criteria such as accuracy, recall, mAP, F1 score, etc., can be used to evaluate the efficiency of the model in

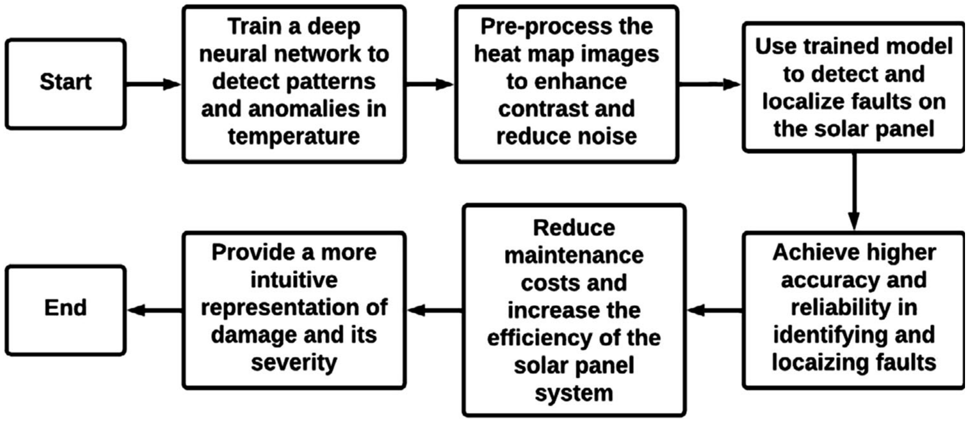


Fig. 8 Detection using heat map images

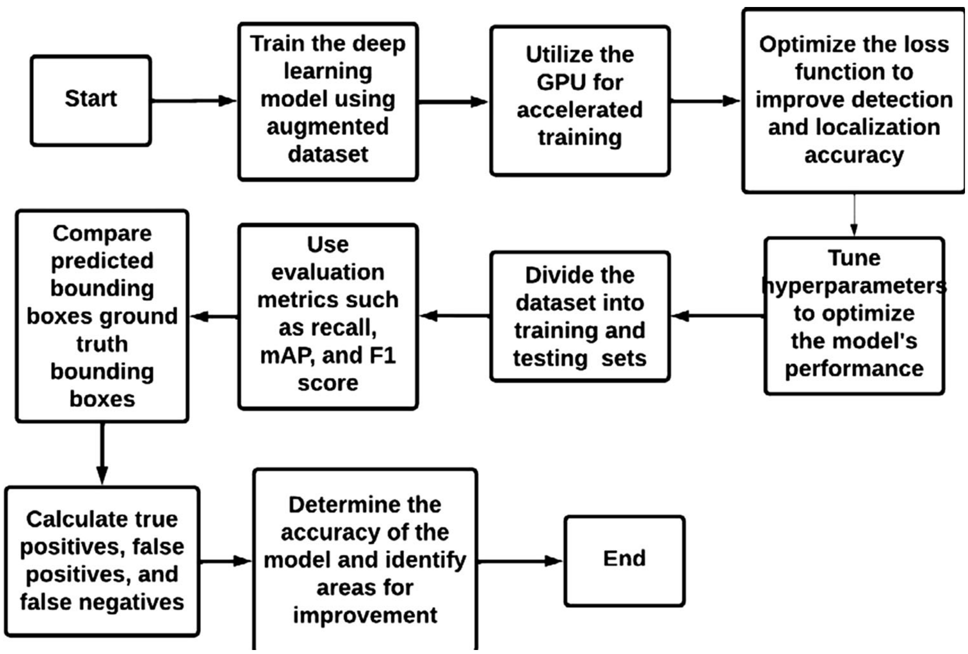


Fig. 9 Training

identifying the damaged solar cells and its local careful evaluation of the model performance how can identify areas for improvement, which can be used to modify the model to increase accuracy. Figure 9 shows the training steps.

After the machine learning model is trained on the training set and tested to confirm its performance on untested data, it should be tested on another test set. This step assures that the model does not overwhelm the training set too much inside and can generalize well. The test set should be different from the training set and should include images that the model has never seen before. To validate the accuracy of the model, predicted scores are assigned to unseen images, which are then compared to ground true scores using metrics such as accuracy, recall, F1 score, accuracy, etc. For example, performs well in the testing process, revealing strong generalizability and acceptability for errors found in real-world solar equipment. The testing procedure is depicted in Fig. 10. If the model performs poorly, it may need to be reevaluated and its design or hyperparameters adjusted.

The applications of solar panel error-based deep learning include configuring the tasks, sequencing the trained models, developing an API, integrating the models with the API, efficiently testing the models, have been installed in a manufacturing facility, and its efforts are monitored in Fig. 11 shows the application.

This dataset intends to provide labeled images of sensors that can be used for automatic damage detection of solar panels and machine learning This diverse and comprehensive dataset will help provide more accurate and effective systems for detecting and mitigating solar panel damage Installations of solar panels can also help reduce maintenance costs and downtime, and provide energy

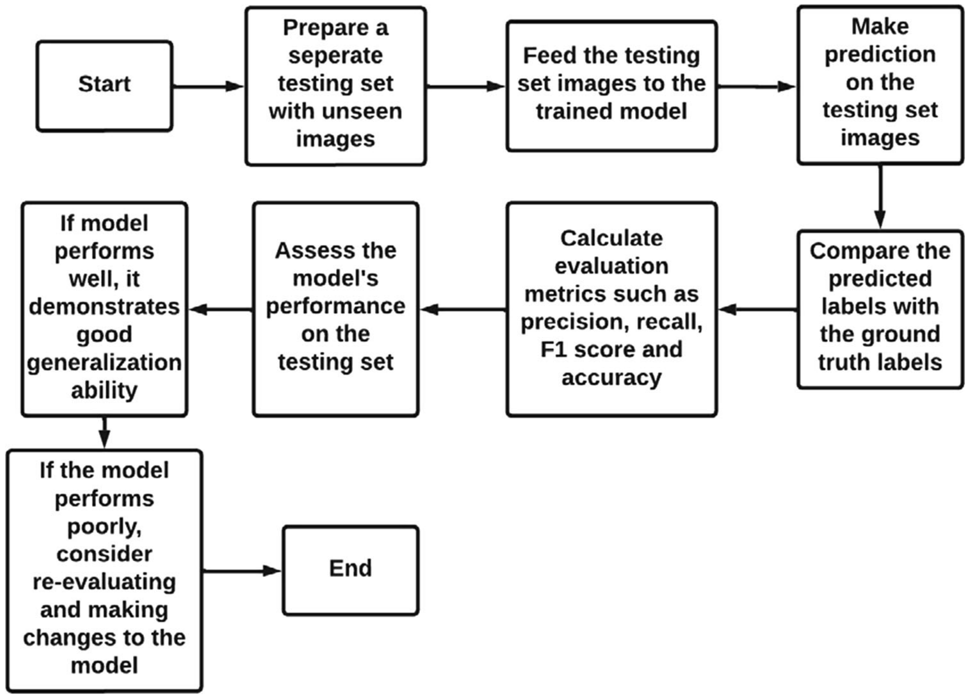


Fig. 10 Testing

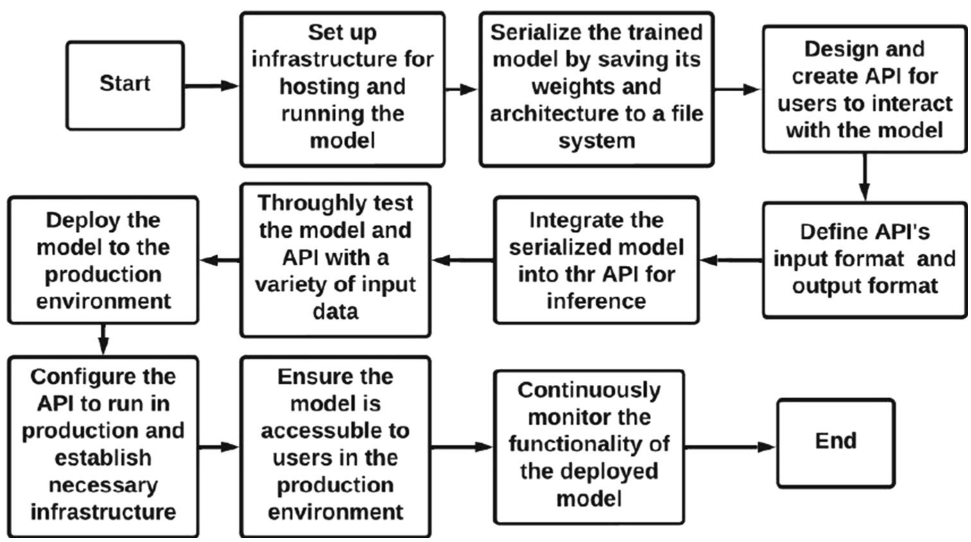


Fig. 11 Deployment
DATASET USED

renewal has been accessible and sustainable. The data set consists of 1509 thermal images, of which 92% were used for training (about 1400 images), the remaining images were retained for testing. Then, data augmentation was applied to the existing data to expand the size of the data set for training. Two types of solar panels were analyzed in this data set: single-cell solar panels and multi-cell solar panels. The data set was grown by three increments per training sample, and the saturation of the images was set from − 15 to + 15%. The brightness of the images studied ranged from − 25 to + 25%, and the brightness of the bright images ranged from − 16 to + 16%.

Results

The trained model has proven to be highly efficient in identifying any damage to both single-cell solar panels (Fig. 12) and multi-cell solar panels (Fig. 13) with great accuracy.

The training results are compared in Table 1. At 0.5 iou, the model has a 0.47 mAP. The model identified and located the bounding boxes for the same. The data set primarily consisted of medium to high object areas that were trained by raising the weight balance of the relevant output layer.

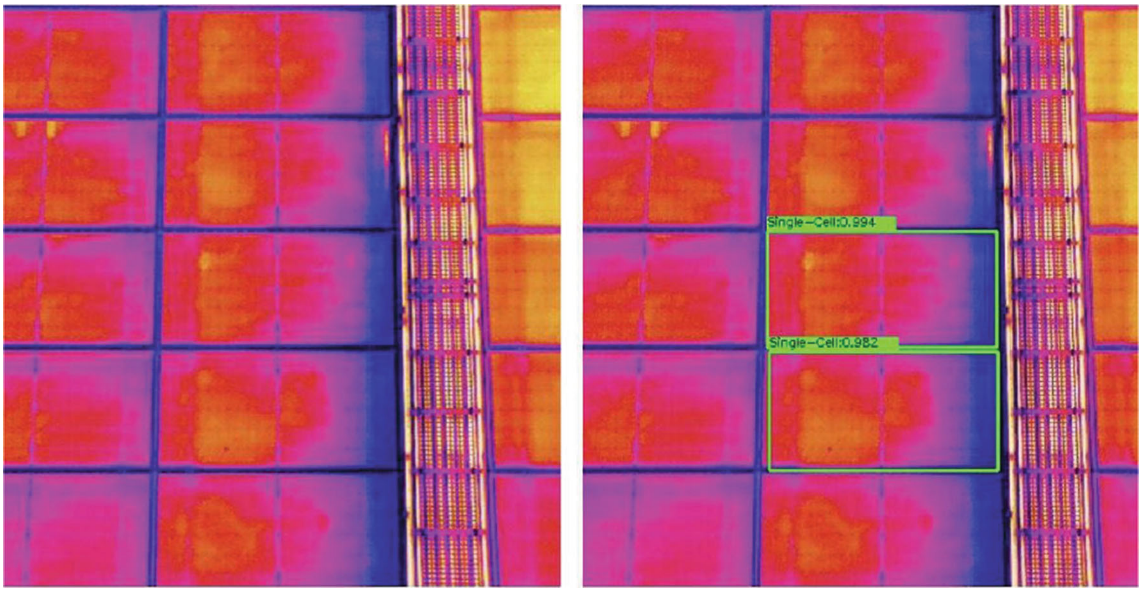


Fig. 12 Model detecting single-cell damage in the solar panel

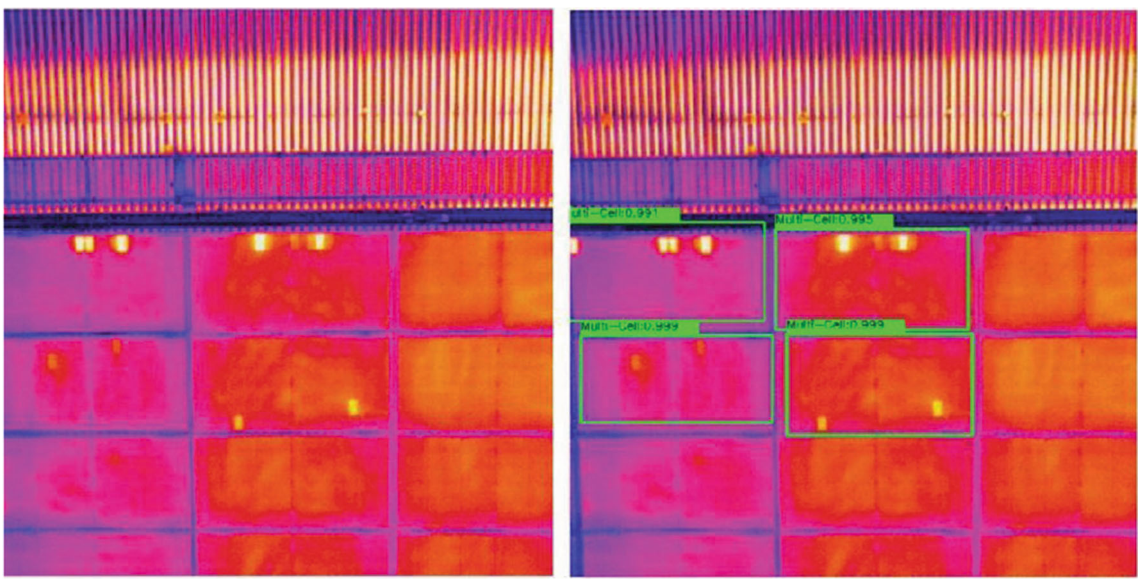


Fig. 13 Model detecting multi-cell damage in the solar panel

Table 1 Results for training

Class	mAP@ 0.5	mAP@0.5:0.95	precision	Recall
Mutli-cell	0.75	0.25	0.53	0.55
Single-cell	0.64	0.26	0.28	0.36
Total	0.69	0.26	0.40	0.46

Table 2 Results of testing

Class	mAP@ 0.5	mAP@0.5:0.95	precision	Recall
Mutli-cell	0.58	0.25	0.53	0.55
Single-cell	0.37	0.26	0.28	0.36
Total	0.47	0.26	0.40	0.46

The model achieved a mean average precision (mAP) score of 0.69 during the training phase, which is regarded to be on the higher end. This suggests that thermal imaging have a relatively good accuracy in identifying and localizing damage in solar panels. The model was trained with 17 million parameters, enabling it to recognize complicated patterns and features in thermal pictures (Table 2).

When tested on a different set of data, however, the model received a lower mAP score of 0.47. This implies that the model's performance may not generalize well to new, previously unknown thermal pictures of solar panels. The testing set's lower mAP score indicates possible difficulties in effectively detecting and localizing damage in real-world circumstances.

In this case, it should be noted that simply increasing the number of parameters does not increase performance. While more parameters may allow for more accurate specification, they also increase the risk of overfitting the training data and may hinder the model's ability to generalize to previously unseen images

Additional optimization techniques may need to be adopted, such as fine-tuning the architecture, including routine methods, or increasing the type and size of the training dataset, may be possible which is needed to further improve model performance This step can help address the issue of overproduction and improve model accuracy.

Conclusion

As a result of our research, a reliable and effective method for locating solar panel damage has been developed. We have made measurable progress in properly identifying and precisely localizing damaged solar panel locations by combining cutting-edge deep learning algorithms, thermal image analysis, and data augmentation approaches. For solar power installations, these improvements result in higher operational effectiveness, lower maintenance costs, and better energy production. Our work highlights the relevance of using technology to solve actual problems in renewable energy systems.

Future Scope

The proposed method can significantly improve existing damage detection models in the future. The method is expected to improve the accuracy and performance in detecting damaged areas by adding additional layers, feature extraction, and using heatmaps instead of infrared images. Data augmentation techniques can be further explored for training datasets in general to generate more robust and successful models, and future research can focus on its validation efforts in real-world situations. Overall, the proposed method has a bright future in damage detection and mitigation.

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