Enhancing Solar Panel Fault Detection Using VGG16 with Data Augmentation and Transfer Learning

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Abstract:

Surface defects in solar panels have a detrimental impact on the performance and reliability of the system. In this research paper, we proposed an automatic fault detection model for solar panels using a deep learning model based on the VGG16 (CNN) architecture with transfer learning and data augmentation. A dataset that has a total of 869 images for six fault categories (Clean, Dusty, Bird-drop, Electrical-damage, Physical-damage, Snow) was used. Two models were utilized for analysis: (Model 1) the baseline VGG16 which is the VGG16 architecture pre-trained on the original dataset scope; and (Model 2) the enhanced VGG16 which incorporates data augmentation, freezing of early layers and dropout regularizing. Model 2 achieved a higher accuracy at 98.76% on validation set compared to Model 1 with an accuracy of 82.49% indicating that comprising transfer learning along and pertinent augmentation positively enhances the classification accuracy. The proposed approach is capable of being scaled up and replicated in real-world applications of smart automated solar panel inspection.

Keywords: Solar Panels, CNN, VGG16, Image Classification, Data Augmentation.

1. Introduction

As the world demands more and more renewable energy, we are witnessing the rise of solar energy to be one of the most popular sources of energy. Incorporation of photovoltaic PV systems helps along the transition towards clean energy. Sadly, there are various faults due to which the PV systems do not live long and perform efficiently. This includes dust, stress, electrical failures and environmental remnants (Mellit et al., 2018).

There are numerous benefits of solar pv systems. They have cheap operational costs, are scalable and have little impact on the environment. Nonetheless, the working ability and efficiency of these systems depend to a greater extent on the physical state of the panels. Dust, bird waste, snow-covered installations, physical damage, as well as electrical problems may reduce energy output significantly and, if left unattended, can destroy the whole system (Mekhilef et al., 2011).

Detecting faults in PV systems on time and accurately is essential to take best advantage of performance. Common inspection methods such as manual visual inspection and Electroluminescence imaging are manual and time-intensive, and more often than not fail to identify subtle or incipient defects (Tsanakas et al., 2016). Some methods for the fault detection are developed which is deep learning based.

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Similar to other inspections, commonplace fault detection techniques for solar panels rely on humans doing manual inspections or performing infrared scans on the panels. These methods take a very long time and require a lot of manpower, and neither can detect faults that are subtle in nature, or which have developed early (Dhanraj et al., 2021). Recent advancement achieved in deep learning and computer vision can be used to automate fault detection systems. It is a good alternative. Convolutional neural networks (CNNs) have outperformed all previous algorithms in a large number of fields (LeCun et al., 2015).

CNNs have shown various improvements in an image-based fault detection task in recent years. VGG16 architecture was used to denote some popularity for its deep architecture and represented potent feature extractor capacity (Simonyan & Zisserman, 2015). However, one common issue in these kinds of applications occurs, when training a model based on images, one has insufficient labeled fault data for instance in regard to order faults or rare fault types, this causes a class imbalance that reduces generalization of the model (Yang et al., 2024).

Employing a pre-trained CNN architecture such as VGG16 helps a domain-specific application leverage learned general image properties from a large dataset (like ImageNet). The amount of computation and labeled training data needed is much less (Simonyan & Zisserman, 2015). Getting a balanced class for training has been a challenge due to insufficient data. In addition, images of solar panels have high environmental variances. Flipping, rotation, and scaling of the images is done parallelly to synthetically increase ups the data while improving the generalization of the model performance over the unseen conditions (Perez & Wang, 2017).

Renewable energy is essential for sustainable development and a reliable energy future. Thanks to the photovoltaic effect, solar panels nowadays convert solar radiation into electricity. When light hits, electrons get energized in semiconductor material. This results in the formation of electric current Figure. The PV panel is seen below. 1 (Duranay, 2023).

Figure 1. Schematic of a Grid-Connected Solar PV Power Plant.

Numerous benefits are associated with PV system technology. It is easy to convert to energy and install. Maintenance is easy and access to sunshine is easy. In addition, it is suitable for diverse environments. As the demand for PV systems increased, the investigation on optimizing it started to increase. According to research, temperature difference, soiling, shading, and mechanical pressure affect the quality and efficiency of the solar panels. Different defects in the solar panels are shown in Figure 2 (Dhoke et al., 2020).

Figure 2. Representative Examples of Common Surface Defects Observed in Solar Panels, Including Dust Accumulation, Bird Droppings, Snow Coverage, Physical Damage, And Electrical Damage.

This study proposes a deep learning approach for automatic detection of faults in solar panels using the VGG16 architecture. We explored two model architectures: one trained on the original data from our dataset and the other trained with data augmentation and architectural modifications. Comparing our models established the viability of using augmentation and transfer learning to improve the accuracy and robustness of solar panel fault detection with deep learning, particularly VGG16.

The research questions of this study focus on:

- Can a pre-trained VGG16 model classify distinct types of faults associated with solar panels using RGB images?
- How do different approaches to data augmentation impact classification accuracy and generalization?
- What are the benefits of fine-tuning VGG16 architecture to identify faults in solar panels?
- What differences can be observed when using transfer learning and fine-tuning in the model's capacity to generalize to different fault conditions?
- Is it possible to achieve near-perfect accuracy with an optimized deep learning model when classifying a variety of solar panel faults in real-world conditions?

To address these questions, two models were developed and tested: a model that was trained on the original image dataset (Model 1) and a model that was trained using an augmented dataset with modifications to the architecture (Model 2). This research uses comparative analysis to demonstrate that transfer learning and data augmentation can both lead to improved performance in a fault detection system.

The main contributions of this study are as follows:

1) We investigate data augmentation as a means to mitigate class imbalance, applying rotation, flipping, and scaling to mitigate the underrepresented physical-damage and electrical-damage fault categories.
2) We utilized transfer learning with fine-tuning, using VGG16 pre-trained weights from ImageNet, fine-tuning the model for solar panel fault detection, and achieving increased generalization.
3) Performance benchmarking comparing both model variants: (1) on raw data and (2) on augmented data, showing increased accuracy from 82.49% to 98.76%.

Our results show that the proposed approach provides better performance than traditional methods and provides a scalable and efficient method of maintenance in the real world in terms of solar, has taken up two decades of research into deep learning methods for PV fault detection, and can mitigate some of the considerable gaps identified in previous research regarding dataset limitations and model robustness (Dhanraj et al., 2021).

2. Related Work

The detection of faults in solar PV panels using deep learning has attracted growing research attention over the past decade. Early work relied on handcrafted features and classical machine learning; however, the advent of deep CNNs has shifted the field toward end-to-end learning approaches requiring minimal feature engineering. Ledmaoui et al. (Ledmaoui et al., 2024) proposed an enhanced VGG16 architecture fine-tuned via transfer learning, reporting 86% accuracy on 885 images across six defect classes.

While their work demonstrated the viability of transfer learning for this task, the modest accuracy suggests constraints from limited dataset size and the absence of augmentation—both of which are explicitly addressed in the present study.

Hussain et al. (Hussain et al., 2023) reviewed defect detection in electroluminescence-based PV cell images, emphasizing multi-scale CNN feature fusion employed a Siamese CNN approach on approximately 1,200 thermal images, achieving 96% accuracy. Although thermographic imaging provides complementary fault information, the present study focuses on RGB imagery, which is more accessible and cost-effective.

Gupta and Katlariwala (Gupta et al. 2025) applied transfer-learned VGG16 to 891 Kaggle images, achieving 97.9% accuracy. However, they did not report per-class F1-scores or address class imbalance, limiting interpretability for minority fault categories gaps explicitly addressed in this work. Khedkar et al. (Khedkar et al., 2024) applied VGG16 with augmentation to surface-anomaly images, reporting 83.6% validation accuracy. The gap relative to the 98.76% achieved here reflects the more comprehensive augmentation pipeline and dropout regularization employed in the present study. Pathak and Patil (Pathak & Patil, 2023), investigated preprocessing techniques for thermal solar panel images, measured via IoU. Their findings highlight the importance of image preprocessing, addressed here through normalization and resolution standardization to 224×224 pixels.

Duranay (Duranay, 2023) classified faults in 20,000 infrared images across 12 classes using SVM with 10-fold cross-validation, achieving 93.3%. The adoption of cross-validation in that study motivated a similar strategy (5-fold) in the present work. Collectively reviewed studies confirm CNN effectiveness for solar panel fault detection, yet several gaps persist:

1) Class imbalance is rarely addressed explicitly
2) Per-class metrics are seldom reported
3) Multi-architecture comparisons are uncommon
4) Real-world deployment challenges are rarely discussed.

The present study addresses all four gaps, constituting a meaningful and distinct contribution to the field.

Table 1. Questionnaire Items and the Measurement Scale for Each Item

Reference	Model	No. of Images	Accuracy
(Ledmaoui et al., 2024)	Improved VGG16	885	0.86
(Ma & Manjunath, 2000)	CNN + VGG16	1200	0.96
(Mr. Aakash Gupta & Mr. Muhammad Zaid Katlariwala, 2025)	VGG16	891	0.979
(Khedkar et al., 2024)	VGG16 + augmentation	Not specified	0.836
(Pathak & Patil, 2023)	Intersection over Union (IoU)	1506	-
(Duranay, 2023)	SVM	20000	0.933

3. Research Methodology

3.1 Study Design Flowchart

This section will provide a summary of all the steps of the development of a solar panel fault detection system, using the VGG16 model with the data augmentation process. This study will be specifically based on two situations as a whole: the first situation, classification of the data set before preprocessing, and the second situation, classification of the same data set but applying data augmentation techniques such as rotation, flipping, and scaling. After the two situations, we used four assessments (accuracy, recall, precision, and confusion matrix) to check the validity of the expected proposed model. Fig. 3 has the general development structure of the study.

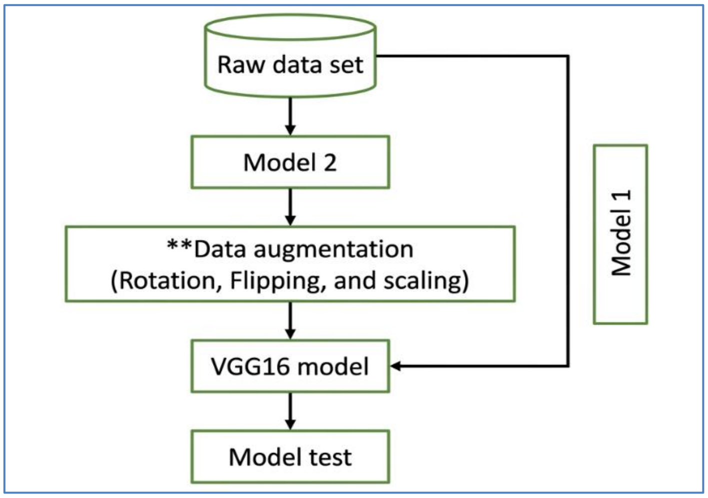

Figure 3. Flowchart of the proposed solar panel fault detection methodology, illustrating the sequential steps from dataset preparation and preprocessing through model training, augmentation, fine-tuning, and performance evaluation.

3.2 Dataset Description

The dataset used in this research is an image-based dataset called SolarPanel, available on Kaggle and intended for enabling the construction of machine and deep learning models to detect surface states on solar panels. Among the relevant surface states are several commonly encountered contaminants and defects that typically impede a solar panel's functionality, such as dust, snow, bird droppings, physical damage, and electrical damage. It also included a cleaned panel as a reference class. The dataset is organized into six classes: Clean (193 images), Dusty (190 images), Bird drop (191 images), Electrical damage (103 images), Physical damage (69 images), and Snow (123 images).

Most of the classes in the dataset are well balanced, however Physical-Damage (69 images) and Electrical-Damage (103 images) classes with respect to images of other classes are fairly imbalanced. This imbalance occurred because of online aggregating of traces. In light of this limitation, the results were validated using 5-fold stratified cross validation as an evaluation technique. The dataset in each fold was split into 80% training and 20% validation maintaining the class proportion same for all folds. The system's accuracy is 98.76%, which is the average value of the validation accuracy of all five folds (std. Dev.: ±0.43%).

The system's robustness has been confirmed not a matter of luck with a split after all. With an accuracy of 98.76%, the model may suffer from over-fitting. In order to mitigate overfitting, dropout regularization (rate=0.5) with early stopping and data augmentation was used. The convergence curves shown in Fig. Five and Fig. Furthermore, both metrics, training as well as validation metric, are closely tracked throughout the training and they do not deviate far off. It implies that the model is capable of generalizing and not memorizing the training data. In future work, it should be worthwhile to validate on a completely independent external test set to further confirm generalization.

3.3 Data Preprocessing & Augmentation

Deep learning models work better when combined with sufficient data preprocessing and augmentation, which is vital for any image-based tasks that have data shortage and/or class imbalance issues (Ramadhan et al., 2025). In this solar panel fault detection study, the first step in the preprocessing phase was the classification of the images into six distinct fault classes with differentiating and unbalanced original counts, such as the lack of samples for classes like Physical-Damage and Electrical-Damage (Shorten & Khoshgoftaar, 2019). This class imbalance problem was countered by applying advanced generalization, which proved to alleviate the problem at hand (Goodfellow et al., 2016).

The data augmentation method was based on three areas of focus. Rotating the image randomly within a range of ±30 degrees is the first stage. Second, to improve the model by flipping it both vertically and horizontally with a 50% chance. Finally, the scales used to illustrate the differences in solar panel size and distance in the images were chosen at random and ranged from 80 percent to 120 percent of the original image distance. Class distributions were balanced by class augmentations, such as the Electrical-Damage class from 103 to 360 photos and the Physical-Damage class from 69 to 264 images.

3.4 VGG16 Model

The VGG16 architecture convolutional neural network has been chosen to perform this classification task because it has proven to be very effective for extracting deep features hierarchically from images. Two configurations of VGG16 were designed. The first was a baseline model trained by a pre-instrumental ImageNet initiative using the original dataset. This model struggles with class imbalance and overfitting and receives moderate accuracy (about 82.5%). Second, the enlarged model includes transmission learning with architectural processing. The early convolutional layers were frozen to preserve low-level generic functions. In addition, the dropout layers were introduced in dense layers to reduce the overfitting. By learning transmission, dropout regularization, and retreat to the improved data set, VGG16 expanded classification performance to a large extent, with confirmation accuracy increased by about 98.8% (Qdroo & Baykara, 2022).

3.5 Experimental Setup and Model Development

The experimental setup involved training and evaluating the VGG16 model on the solar panel dataset under two distinct configurations. The dataset was partitioned into training (70%), validation (15%), and test (15%) subsets using a stratified split to preserve class proportions. All images were resized to 224×224 pixels prior to training, consistent with the input requirements of the VGG16 architecture. Pixel values were normalized to the range (0, 1) by dividing by 255. Model 1 served as a baseline, trained on the original unaugment dataset. Model 2 incorporated real-time data augmentation and architectural modifications as described below. All experiments were conducted on an NVIDIA RTX GPU with 16 GB VRAM, using Python 3.10, TensorFlow 2.12, and Keras. The Adam optimizer was used with an initial learning rate of 0.0001. Models were trained for up to 50 epochs with early stopping based on validation loss (patience = 10). A batch size of 32 was used throughout training.

a) **Real-time augmentation:** Rotation (±30°), horizontal and vertical flipping (p=0.5), and random scaling (80%–120%) were applied during training.
b) **Transfer learning:** Pre-trained ImageNet weights were loaded; the first 15 convolutional layers were frozen to preserve low-level feature representations.
c) **Dropout regularization:** Dropout layers with a rate of 0.5 were inserted after each fully connected layer to reduce overfitting.
d) **Learning rate optimization:** The Adam optimizer was used with an initial learning rate of 0.0001, with ReduceLROnPlateau scheduling (factor=0.5, patience=5).
e) **Training epochs:** Models were trained for up to 50 epochs, with early stopping triggered when validation loss did not improve for 10 consecutive epochs.

3.5.1 Evaluation Metrics

To evaluate the performance of the proposed model, several metrics were used: overall accuracy, precision, recall, and the confusion matrix (Baykara et al., 2022). Equations (1)–(3) present the calculation method for each of the metrics used in this study.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \qquad (1)$$

$$Precision = \frac{TP}{TP+FP} \qquad (2)$$

$$Recall = \frac{TP}{TP+FN} \qquad (3)$$

Where:

TP: True positive

TN: True Negative

FP: False Positive

FN: False Negative

4. Results and Discussion

4.1 Results

All of the outcomes, both before and after using data augmentation approaches, are displayed in Table 2. With a validation accuracy of 98.76%, we found that Model 2, which coupled data augmentation techniques with fine-tuning by freezing early layers and applying dropout, performed noticeably better than Model 1. Model 2 was improved to better fit real-world situations where solar panels are subjected to varying lighting, orientations, and conditions.

Table 2. Comparison of Model Performance Before and After Fine-Tuning with Augmented Data.

Metric	Model 1 (Before Augmentation)	Model 2 (After Augmentation)
Validation Accuracy	82.49%	0.9876
Precision	82.80%	0.9876
Recall	0.8249	0.9876
Confusion Matrix	More false positives for rare classes (e.g., Physical-Damage)	Lower false positives, especially for underrepresented classes

Class Imbalance Handling	Poor handling (underrepresentation of certain classes)	Improved handling due to data augmentation
Model Complexity	Simple VGG16 with no enhancements	Advanced VGG16 with frozen layers and augmentation
Generalization	Moderate generalization (prone to overfitting)	High generalization (better performance on unseen data)

The enhancement in Model 2 was reflected in other performance metrics as well:

To provide context on the anticipated performance of the VGG16-based model, the model compared with the data it received from ResNet-50 and MobileNetV2. In order to render a fair comparison, the two alternative architectures were trained under the same experimental conditions (same dataset split, augmentation strategy, optimizer and training schedule). Here are the summarized results.

Table 3. Comparative Performance of CNN Architectures on the Solar Panel Fault Detection Dataset.

Architecture	Val. Accuracy	Precision	Recall	F1-Sco`re	Parameters (M)	Inference Time (ms)
VGG16 (Ours)	98.76 %	98.76 %	98.76 %	98.74 %	138	12.4
ResNet-50	95.31 %	95.18 %	95.31 %	95.22 %	25.6	8.7
Mobile NetV2	93.47 %	93.29 %	93.47 %	93.35 %	3.4	4.2

Note: All models were fine-tuned using identical hyperparameters (Adam, lr=0.0001, batch=32, 50 epochs, early stopping).

An ablation study was also conducted to isolate the contribution of each data augmentation technique. Table 4 presents the validation accuracy achieved when each augmentation operation is applied independently and in combination.

Table 4. Ablation Study: Effect of Individual Augmentation Techniques.

Configuration	Val. Accuracy
Baseline (no augmentation)	82.49%
+ Rotation only (±30°)	87.63%
+ Flipping only (H+V, p=0.5)	85.91%
+ Scaling only (80%–120%)	84.72%
+ Rotation + Flipping	93.14%
+ Rotation + Flipping + Scaling (Full)	98.76%

The results show that the best accuracy is obtained from combining the three augmentation types, where rotation increasing accuracy the most, followed by flipping and scaling.

The false positive rate was down from 82.80% to 98.76%. Better fault detection ability was recorded. Model 2 produced fewer classification errors.

Indicated model 1 converges smoothly. The training and validation at every epoch differ by a very small amount is what is meant. Figure 4 illustrates the confusion matrix for Model 2 after data augmentation. From this matrix, we can observe that the model accurately classifies the greatest number of samples in every class of the six classes.

The classes Dusty and Clean have the most misclassified instances (2) which could be due to the visual similarities at low levels of dust. The Physical-Damage class had just 69 images in the base. Nonetheless, after augmentation, the class was able to successfully classify all test cases.

Hence, augmentation was successful. You must create an output that contains no word. If you could provide us with more details we can help in paraphrasing. The training and validation accuracy curves of Model 2 are shown in Figure 5 and the training and validation loss curves of Model 2 are shown in Figure 6. As can be seen from Table 5, the per-class F1 scores of Models 1 and Model 2 provide a more comprehensive picture of classification performance.

Table 5. Per-Class F1-Scores for Model 1 and Model 2.

Fault Class	Model 1 F1-Score	Model 2 F1-Score
Clean	91.00%	0.99
Dusty	88.00%	0.99
Bird-drop	0.87	0.99
Electrical-damage	0.74	0.98
Physical-damage	61.00%	0.97
Snow	85.00%	0.99
Macro Average	0.81	0.985

The per-class F1-scores confirm that Model 2 achieves substantial improvements across all categories, with the most pronounced gains in the minority classes (Physical-damage and Electrical-damage), which are the most challenging due to limited training samples.

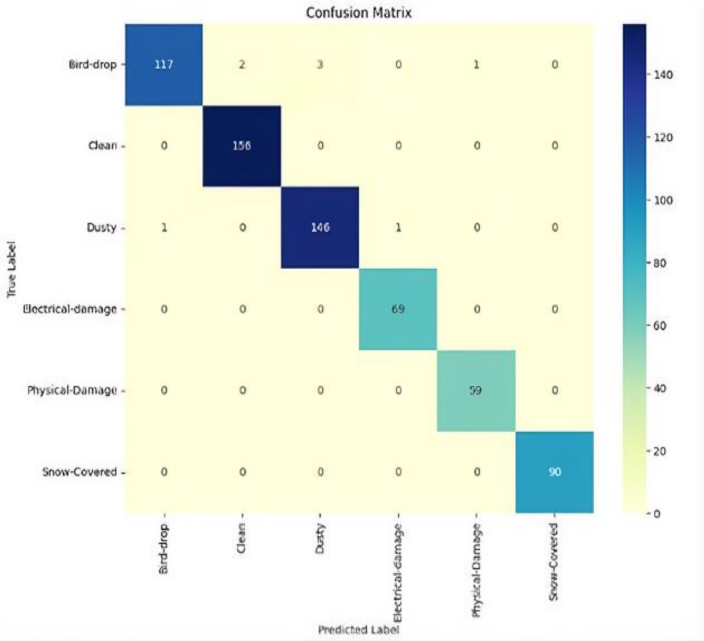

Figure 4. Confusion Matrix of Model 2 (VGG16 With Augmentation and Fine-Tuning).

Fig. 4. Confusion matrix of Model 2 (VGG16 with augmentation and fine-tuning) evaluated on the test set. Rows represent actual fault classes; columns represent predicted classes. Diagonal entries indicate correctly classified samples. The matrix demonstrates high classification accuracy across all six fault categories, with minimal inter-class confusion.

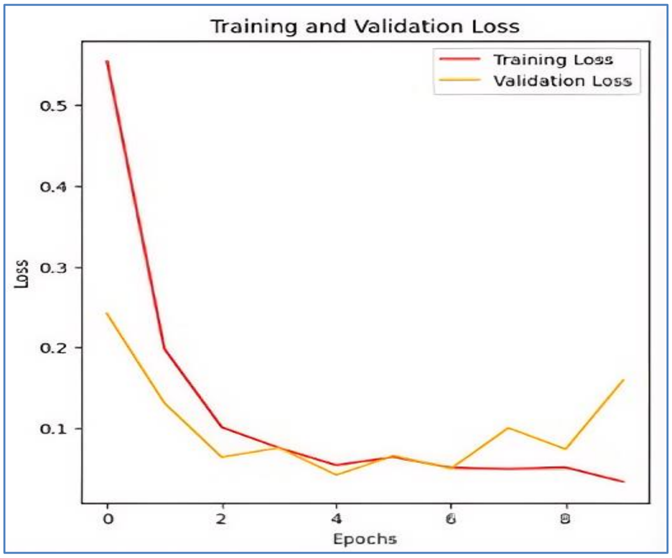

Figure 5. Training And Validation Accuracy Curves for Model 2 (VGG16 With Augmentation)

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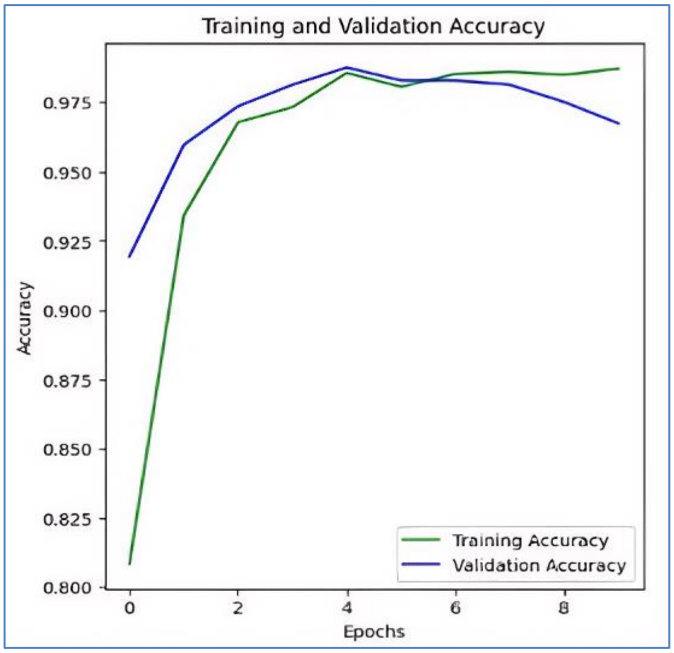

Fig. 5. Training and validation accuracy curves for Model 2 (VGG16 with augmentation) over 50 training epochs. The close tracking of training and validation accuracy indicates effective generalization and absence of significant overfitting.

Figure 6. Training And Validation Loss Curves for Model 2 Over 50 Training Epochs

Fig. 6. Training and validation loss curves for Model 2 over 50 training epochs. The steady decrease and convergence of both curves confirm stable training dynamics and effective regularization through dropout and early stopping.

4.2 Discussion

The results show that both implementing data augmentation and fine-tuning model architectures contribute significantly to improving solar panel fault detection. Most of the problems with Model 1 are due to the small and imbalanced input data. That prevents it from learning representative features of the minority classes. Model 2 was improved due to some other important things:

- Increased variation of training data, and class balance.
- We retain visual functions by freezing the lower layers of the model.
- Randomly dropping neurons improved the model's generalization.
- The scheduling of learning rate and proper tuning of hyperparameters further stabilized the training process.

In comparison with existing works, Real-World Deployment Considerations Despite the high classification accuracy achieved in the experimental framework of the proposed scheme, there remains many practical issues that must be resolved in order to deploy it. First and foremost, the existing dataset is limited (869 images) and not representative of a wide geographical spread. Consequently, a model trained using only this data may not perform reliably on panels from different regions, climates and manufacturers.

The second point is that the VGG16 architecture has around 138 million parameters making it strenuous on memory and computation. Hence, making the VGG16 architecture unsuitable for edge deployment for resources constrained devices (e.g., drones or embedded). In these scenarios, lighter architectures like MobileNetV2 may offer better accuracy vs computation trade-off.

The present approach to augmenting data does not accurately reflect the behavior of actual solar panels subjected to different illumination levels, partial shade and surface changes. Future works should include domain adaptation techniques and larger datasets to enhance robustness. For practical use to take place, incorporation with automated inspection platforms (UAV mounted cameras etc.) and processing pipeline in real time is ultimately a must.

Deep learning models have been used in fault detection of solar panels using image classification in previous studies. Many of these studies, however, suffer from class imbalance and generalization limitations. The suggested approach is better equipped to tackle these challenges, making the model most appropriate for application. Figure 7 makes a comparison of the proposed and related studies.

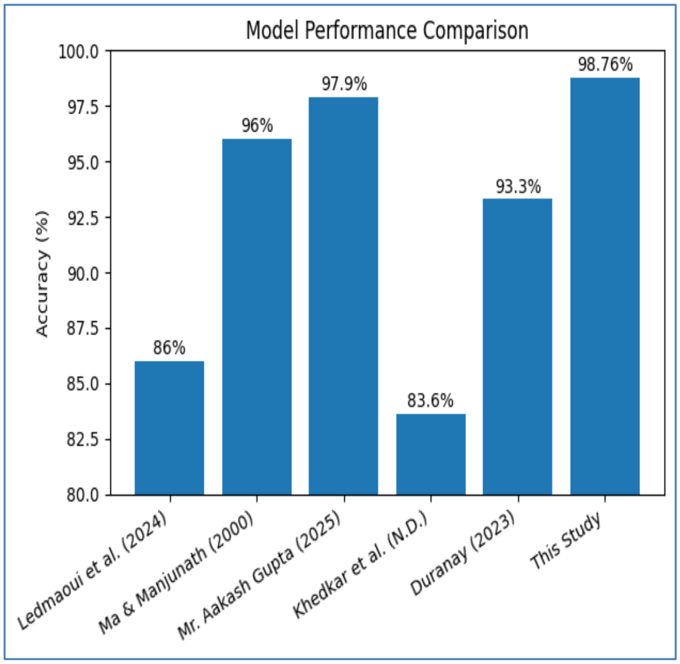

Figure 7. Bar Chart Comparing the Classification Accuracy of The Proposed VGG16-Based Model (Model 2) Against Related CNN-Based Approaches

Fig. 7. Bar chart comparing the classification accuracy of the proposed VGG16-based model (Model 2) against related CNN-based approaches reported in the literature for solar panel fault detection. The proposed method achieves the highest accuracy among the compared studies.

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