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Efficient Net Driven Smart Detection of Dust Accumulation on Solar Panels

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Abstract

The accumulation of dust on PV panels results in reduced energy efficiency and output power from the panels. This work proposes an effective dust detection system using the EfficientNet-B0 convolutional neural network (CNN) model. Channel normalization and data cleaninghave been incorporated to enhance accuracy. The proposed system categorizes panels into clean and dusty categories. The EfficientNet B0 architecture ensures high accuracy (88%) with minimal computational complexity. This method enables hands-on maintenance and reduces the need for manual inspection. The system also ensures enhanced solar energy production.

Keywords: Dust Accumulation, Solar Panel, EfficientNet-B0, CNN, Accuracy.

1. Introduction

Traditional power generation methods that depend on fossil fuels are shifting towards Renewable Energy Sources (RES) with the goal of achieving zero greenhouse gas emissions by 2050. RES not only has the potential for cost savings but also maintains environmental sustainability. Among these, solar is renowned due to its cleanliness and abundance [1], [2].

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Thus, the global implementation of photovoltaic (PV) technology is anticipated to grow considerably, offering a promising and eco-friendly substitute for fossil fuels.

Individual industries can produce solar energy by installing PV panels to generate electricity for their needs. This allows for independent power generation of electrical energy [3]. Despite major advancements in PV panel technology, numerous challenges exist that diminish their efficiency and cause system failures.

The accumulation of dirt on the PV panels can significantly affect their power output. The panels consist of organized components that are prone to pollution and environmental factors. Residues of pollution (ie. dirt etc.,) can block some cells within the PV module, leading to reduced efficiency and a shorter lifespan. This blockage can also influence the overall performance and resultin long-lasting degradation of the module. Therefore, it is important to formulate an effective method for cleaning and monitoring these panels to enhance module efficiency and lower maintenance costs.

However, the manual cleaning and examination of PV panels can be labor-intensive, costly, and unfeasible in larger solar farms. Thus, forming an automated monitoring system is vital for maintaining optimal panel performance. Recent advancements in deep learning (DL) have created new prospects for non-invasive, image-based dust detection methods [4, 5]. This study suggests using Efficient Net, a CNN architecture, to detect dust accumulated on PV panels. Efficient Net is renowned for its high accuracy and computational efficiency, making it ideal for real time applications. By training the model on labeled images (ie. clean and dusty panels), the system can automatically classify the dusty panels.

The major goal is to formulate a reliable solution that assists in analytical maintenance and minimizes energy losses. Integrating DL based topology into PV systems can enhance both their operational efficiency and lifespan.

2. Related Work

The dust detection in PV using Artificial Intelligence (AI) has achieved greater popularity. Apart from that, numerous methods, including Machine Learning (ML) have been introduced for the detection of dusty panels. Computer vision has been incorporated for the detection of dust particle sizes [6]. Similarly, ML techniques like Random Forest (RF) [7], and k-nearest neighbors (kNN) [8] have been designed for particle identification. DL has been tailored for dust detection on PV panels.

An Artificial Neural Network (ANN) based model has been formulated using image data retrieved from dusty panels. Additional parameters, namely irradiance, were measured using multimeters and LDR sensors [9]. A CNN has been modelled for dust detection, incorporating web-supervised learning for classifying soiling types based on predicted localization masks [10]. This approach utilised Bi-directional Input-Aware Fusion (BiDIAF), resulting in a 3% improvement in power loss prediction and a 4% gain in localization accuracy.

To predict the uneven dust concentration, ResNet was tailored and achieved an R^2 and MAE of about 78.7% and 3.67% [11]. A modified LeNet CNN model has been incorporated for PV dust detection, achieving a higher accuracy (80%) and a mean squared error (MSE-0.0122) [12].

AlexNet, VGG-16 and LeNet were proposed for PV panel dust detection. The dataset utilised in this topology comprises 599 image and among these three, AlexNet achieved a higher accuracy of about 93.3% [13]. In dust detection, a deep belief network was also found to outperform conventional ML approaches [14]. Both MobileNet and VGG-16 were integrated to improve both panel valuation and maintenance [15].

AE-LSTM, Facebook Prophet and isolation forest models were also utilised for PV panel analysis [16]. A modular neural network was incorporated to evaluate the impact of dust and temperature on PV modules [17].

Despite their efficacy, conventional DL models exhibit computational expenses and extensive parameter sizes, which make them unsuitable for PV panel monitoring. These methodologies tend to overfit, when they are utilised for small datasets and under different environmental conditions like lighting etc. To address these limitations, EfficientNet has been introduced as a feasible alternative, which balances all parameters (resolution, depth, and width). It realizes higher precision and less computational complexity. It also simplifies transfer learning and makes it more suitable for dust detection with limited training data.

The core contributions of this work are:

- Development of Efficient Net-B0 for higher accuracy with less computational complexity.

- Assessment of this method is proven by comparing its effectiveness with other DL topologies.

Thus, this research examines the significant advancement in PV panel maintenance by introducing an EfficientNet-B0 model. This system enables automated, real time monitoring of PV panels and eliminates the need for manual inspection. The high accuracy with low computational cost, makes it suitable for dusty panel detection. This improves energy output with reduced operational costs and supports sustainable energy practices. It is scalable and adaptable, even with limited training data. Overall, it contributes to smarter, cleaner and more efficient PV panels for electricity production.

3. Methodology

Thus, the methodology adopted for the proposed work is depicted in figure 1.

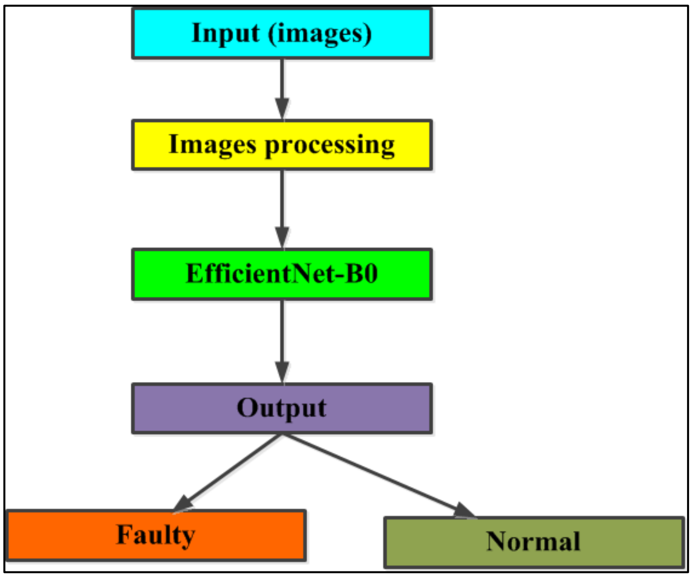

Figure 1. Methodology

Figure 1 illustrates a fault detection system using DL. Initially, images are input into the system. These images undergo a preprocessing phase, including resizing, normalization and noise removal. The preprocessed images are then fed into an EfficientNet-B0 model, a lightweight and accurate CNN architecture. EfficientNet-B0 processes the visual data to extract important features. Based on this feature extraction, the model generates an output prediction. The output is classified into two categories: "Faulty" or "Normal." If abnormalities are detected in the image, the system flags it as faulty; otherwise, it is considered normal. This approach enables efficient, automated fault diagnosis using image-based deep learning.

3.1 Dataset

The dataset, which contains images of the PV panels, was extracted from a Kaggle dataset. This dataset comprises different types of panel images, such as Clean, Dusty, with Bird Droppings, Physical Damage, and Snow Covered. Some of the sample images obtained from the dataset are depicted in figure 2.

However, in this research, only images categorized as Clean and Dusty were utilised to train the EfficientNet-B0 model. Out of a total of 206 images selected, 122 were labeled as Clean and 84 as Dusty, resulting in a fairly balanced dataset for binary classification. This distribution of classes was selected to ensure a practical dataset size while emphasizing the key conditions that impact solar panel efficiency.

3.2 Preprocessing

The collected dataset is stored in a dataframe. The dataset includes images of different sizes, which, in turn, generates an imbalance in the dataset. To overcome this, the obtained images are modified into 3 channel square shaped images of size 224×224×3.

- **Channel Normalization**

Each RGB image was normalized by scaling pixel values from [0, 255] to [0, 1], to accelerate convergence.

- **Noise Removal**

Image denoising was performed using a Gaussian blur filter, which helps reduce random sensor noise.

- **Data Cleaning and Label Verification**

Low-quality images were removed, and image labels were manually cross-verified to ensure dataset integrity. Finally, a total of 206 images were finalized for training and testing sets. These images were carefully selected to ensure quality, accurate labelling, and balanced representation of both faulty and normal classes.

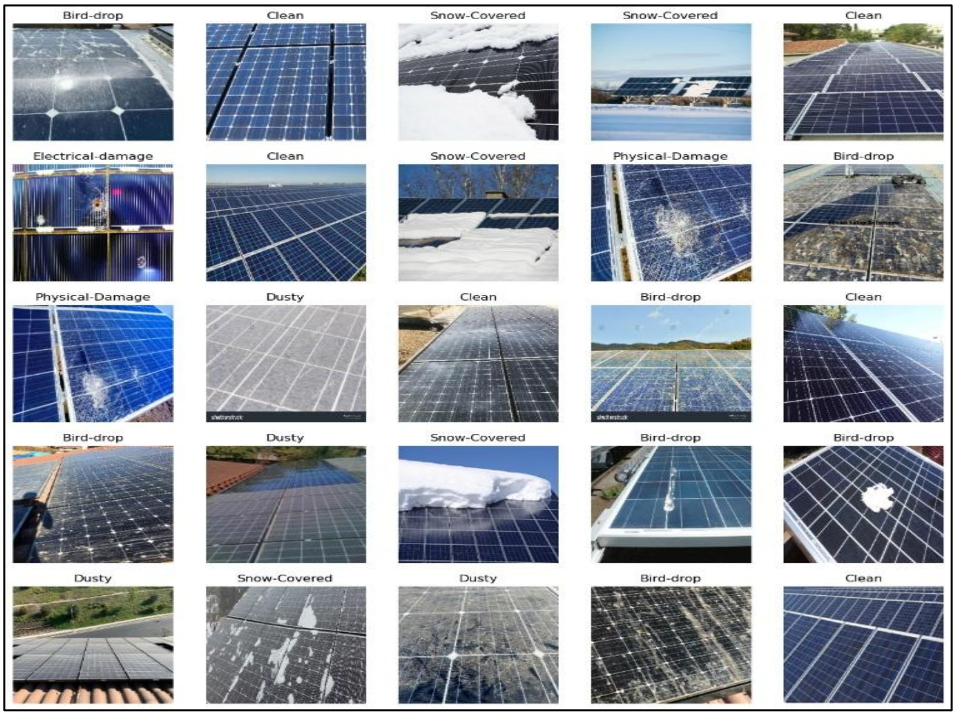

Figure 2. Sample Dataset Images

3.3 Transfer Learning

It is a technique utilized in ML where a pre-trained model, developed for some other application, can be adapted for a different but related application. Thus, in the image classification process, topologies like ResNet, and EfficientNet are pre-trained on ImageNet and then fine-tuned according to the specific domain. It speeds up the training process with improved accuracy, and reduces the overfitting problem. It is more effective in cases where labeled data is limited. while reusing the learned features (edges, textures, and patterns), it helps the models to generalize better. Hence, this study integrates EfficientNet B0 to ensure a balance between efficiency and classification accuracy.

3.4 EfficientNet

EfficientNet introduces compound scaling to enhance its performance. Its main objective is to improve the system's performance with a reduced number of Floating Point Operations per Second (FLOPs).

However, in CNNs, increasing the number of layers is more challenging. The selection of the optimal combination manually is a time-consuming process. In EfficientNet, this process is managed through compound scaling. Hence, greater performance is achieved through scaling.

Additionally, it automatically adjusts the network dimensions—depth, width, and resolution—using a compound coefficient. This methodology ensures systematic and principled scaling of the network.

The proposed model, EfficientNet-B0, increases the size of the network's depth, width, and image size by factors αN, βN and γN. α, β, and γ are predetermined coefficients, selected through a modest grid search conducted on a smaller model. With the insertion of the compound coefficient ϕ, balanced scaling across all dimensions is ensured. When incorporated for a larger dataset, it is necessary to use deeper networks to expand the receptive field and widen the channels to capture fine details from the enlarged images.

Thus, the fundamental architecture of EfficientNet-B0 is constructed using the inverted bottleneck residual blocks initiated in MobileNetV2,

Figure 3 represents the building blocks of Efficient Net B0.

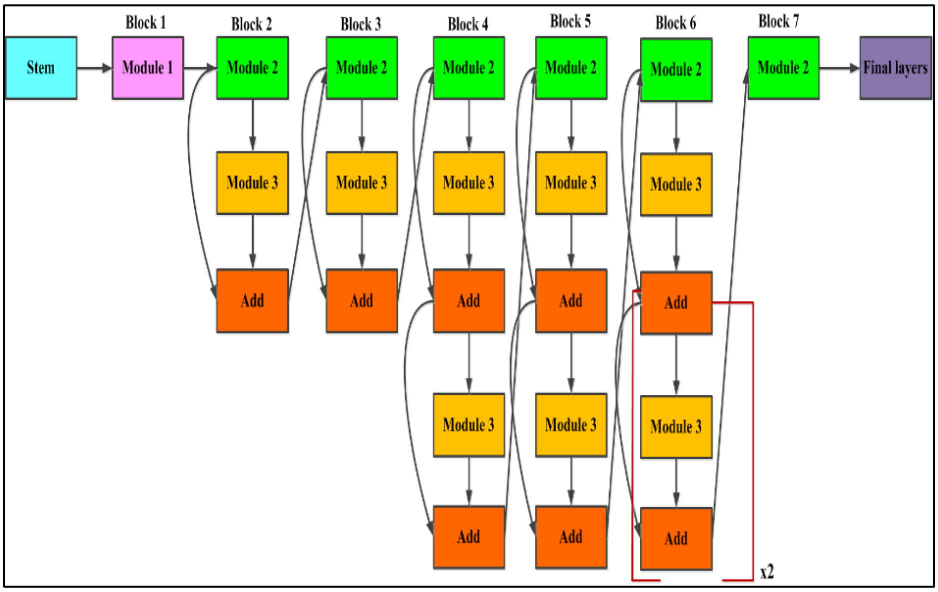

Figure 3. Architecture - Efficient Net B0

The Stem layer performs an initial feature extraction, followed by a sequence of seven blocks. Each block contains a combination of Module 1, 2 and 3. These modules are unified with residual connections to preserve gradient flow and improve training stability. Each module's output is delivered to an "Add" operation and thus integrates the residual information before feeding into the next block. Block 6 comprises two iterations. Its main function is increasing the network's depth without any modifications in parameters. The final block of this unit is Block 7, where classification takes place. This design allows EfficientNetB0 to be both highly accurate and computationally more efficient.

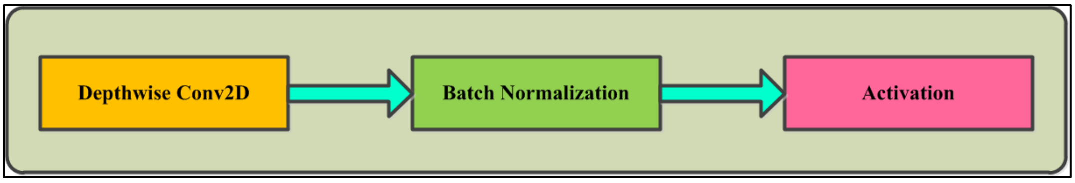

Figure 4. Module 1

Figure 4 depicts the structure of module 1. It comprises three layers, Depthwise Conv2D, Batch Normalization, and an Activation function. The Conv2D utilises distinct filters for each input channel and decreases the computational load. Batch Normalization, normalizes activations to speed up the training process. An Activation function (ReLU) adds non-linearity, allowing the network to recognizeintricate patterns. This setup ensures efficient feature extraction

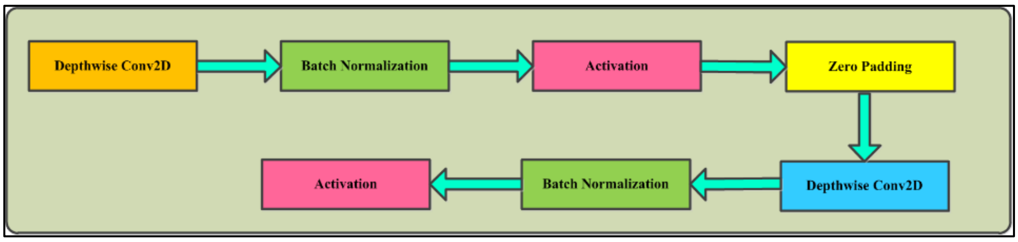

Figure 5. Module 2

Figure 5 depicts the blocks of module 2. In this module, a Depthwise Conv2D executes filtering for each channel. Both Batch Normalization and a non-linear activation function are carried out along with zero padding. The zero padding preserves spatial dimensions. This padded output undergoes the same process once more for spatial feature extraction, effectively capturing spatial characteristics with low computational expense.

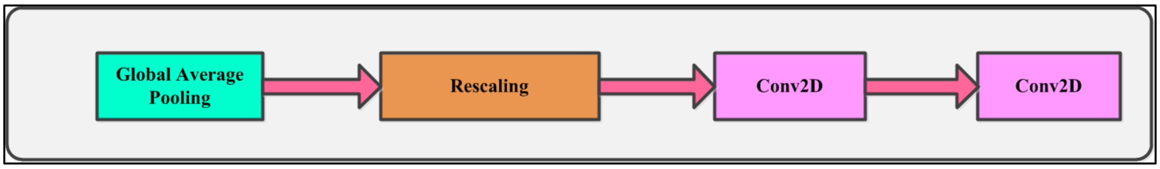

Figure 6. Module 3

Module 3, depicted in Figure 6 performs feature recalibration. Global Average Pooling, is incorporated to reduce each feature map into a single value by computing its average, summarizing global spatial information. A rescaling layer is untiled to adjust the values to prepare them for modulation. In this module, a Conv2D layer acts like a fully connected layer of SE blocks. A second Conv2D layer is tailored to restore the original channel dimensions. This network is more focused on informative features. The parameter settings of this DL are depicted in table 1.

Table 1. Parameter Settings

Hyperparameter	**Value**
Optimizer	Adam
Learning Rate	0.001 (1e−3)
Batch Size	16
Number of Epochs	50
Dropout Rate	0.45
Loss Function	Categorical cross entropy
Validation Split	10% of training set

4. Results and Discussion

This section deliberates the results of the proposed system. The model's performance was examined on unseen test data and evaluation metrics (precision, recall, F1-score, sensitivity / specificity) were analysed to assess the effectiveness of the proposed net. Figure 7 portrays the accuracy and loss curve of the proposed system.

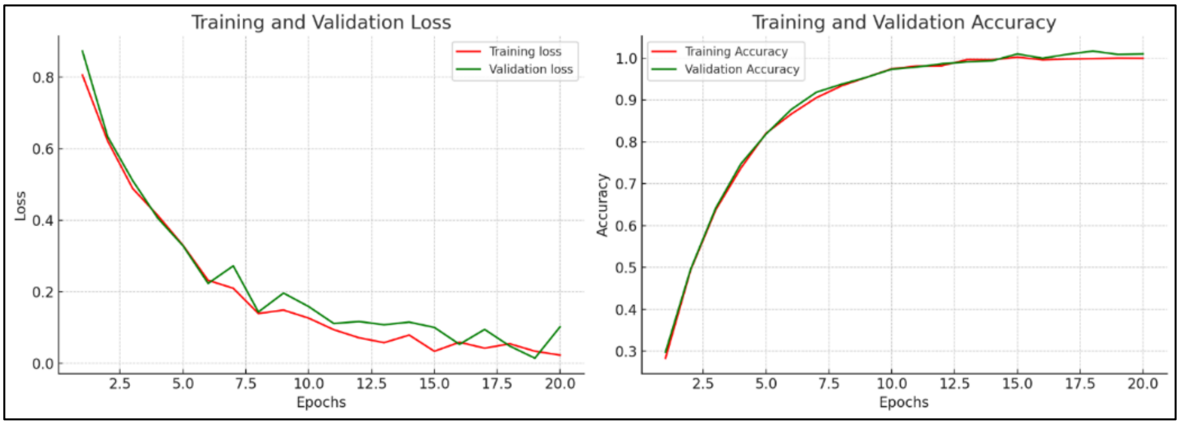

Figure 7. Loss and Accuracy Curve

From the loss curve, it is evident that the proposed system exhibits low overfitting. The training accuracy reaches nearly 100% whereas the validation accuracy also remains high but depicts small fluctuations. These curves reveal that the model is well-tuned. The performance gain appears to be constant around the 15th epoch itself.

The confusion matrix is essential because it provides a detailed performance of the classification model by displaying correct and incorrect predictions for each class. It also identifies the specific types of errors.

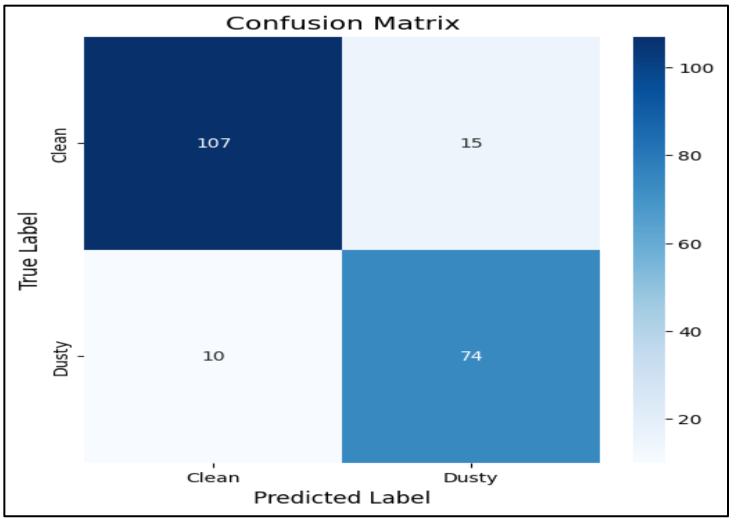

Figure 8. Confusion Matrix

From the figure 8, it is evident that the model performs well in differentiating between the "Clean" and "Dusty" classes. Out of 122 clean samples, 107 were correctly classified, while 15 were misclassified as dusty. Similarly, of the 84 dusty samples, 74 were correctly predicted and 10 were incorrectly labeled as clean. Thus, the model achieved an overall accuracy of approximately 88%. Precision for the "Clean" class was about 91%, while recall was 88. For the "Dusty" class, precision was slightly lower at 83%, but recall remained at 88%. Thus, these results indicate a balanced and reliable classification performance across both classes.

Table 2. Classification Report

	Precision	**Recall**	**F1-Score**	
Clean	0.911	0.884	0.901	122
Dusty panel	0.834	0.885	0.865	84
Accuracy			0.880	206
Macro avg	0.871	0.885	0.881	206
Weighted avg	0.889	0.886	0.881	206

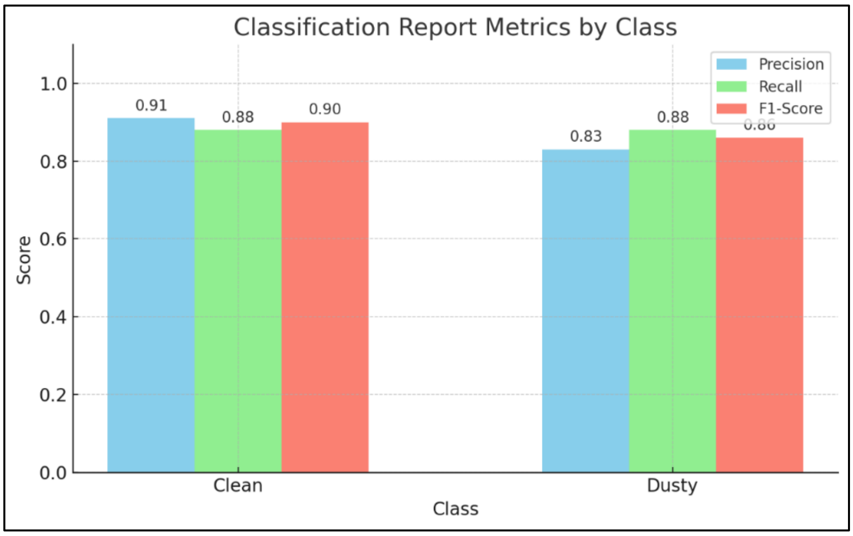

Figure 9. Classification Report

The classification report (in Table 2 and Figure 9) represents the performance of a model in distinguishing Clean and Dusty panels. The overall accuracy of the model is 88%, indicating that it correctly classified 88% of all test samples. For the Clean class, the model achieved a precision of 0.91, recall of 0.88, and F1 score - 0.90, which depicts the model reliability in identifying clean instances. Similarly, the Dusty class exhibits a precision of 0.83, recall of 0.88 and F1score of about 0.86. This precision score of Dusty class suggests that there may be some misclassification of clean samples as dusty. The macro average F1-score (0.88), indicates balanced performance across both classes, whereas the weighted average F1-score (0.88), reveals the model's effectiveness. Overall, the model performs well for both categories. Similarly, the execution time of the proposed algorithm is about 39 ms.

Classification error refers to the incorrect predictions made by a classification model. In this case, the error is approximately 12%, as the model misclassified 25 out of 206 samples.

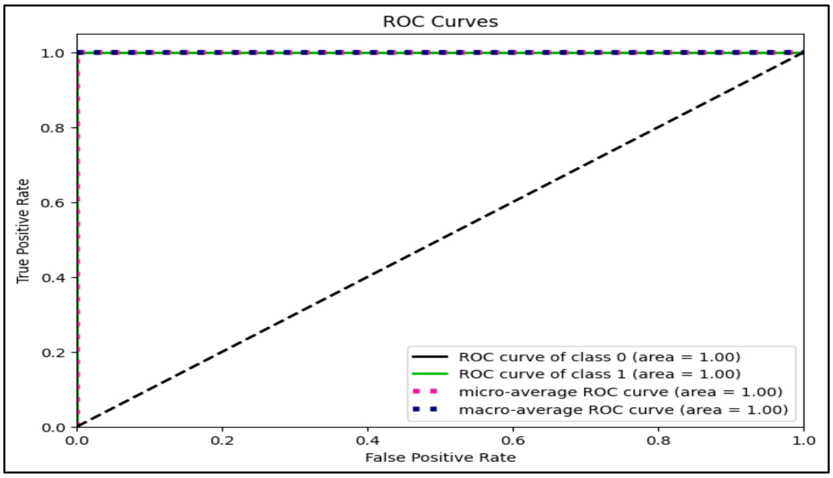

Figure 10. ROC Curve

Figure 10 represents the classification performance of the model. From figure 10, it is perceived that the model has achieved a True Positive Rate (TPR) of 1.0 and a False Positive Rate (FPR) of 0.0 hence, it is proven that there is zero misclassifications in both classes. These curves depict that the model can distinguish the two classes without any uncertainty.

5. Comparison Analysis

Table 3. Comparative Analysis

Topology	Accuracy (%)
VGG16	79.1
ResNet50	82.45
Proposed	88

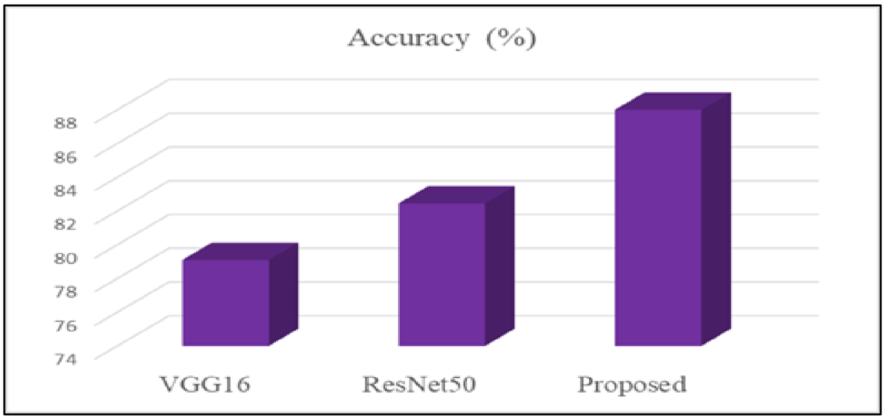

Figure 11. Comparative Analysis

From the table 3 and figure 11, it is observed that the proposed model outperforms other architectures, achieving an accuracy of 88% compared to 82.45% for ResNet50 and 79.1% for VGG16. The results confirm its superiority in dust detection.

6. Conclusion

In this study, an image-based dust detection system for PV panels was formulated using EfficientNet-B0 DL model. It achieves an accuracy of about 88% which is greater than other topologies in the classification of clean and dusty panel. The results confirm its superiority in dust detection. By employing this automated approach, PV panel maintenance becomes more efficient and results in reduction of performance losses. Thus, it reduces dust accumulation by up to 30–40%.

However, the major limitation is the smaller dataset (206 images), which may affect the model's generalizability. Apart from that, it only classifies panels as clean or dusty, omitting other conditions like bird droppings and physical damage. Thus, expanding the dataset and designing the model to classify different levels of dust can further improve accuracy and operational efficiency. In the future, it can be integrated with IoT mechanisms for real-time maintenance. It can be optimized using edge devices like Raspberry Pi to enable on-site processing.

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