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# A Deep Learning Approach for Fault Detection in Photovoltaic Systems Using MobileNetV3

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**Keywords**

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**Abstract**

This study investigates the use of the MobileNetV3 deep learning architecture for fault detection in photovoltaic (PV) systems. The research developed a model capable of classifying solar panels under six different conditions: clean, physically damaged, electrically damaged, snow covered, bird droppings covered, and dusty panels. Using a dataset obtained from Kaggle, pre-processed and divided into training (70%) and test (30%) sets, the MobileNetV3 model achieved a validation accuracy of 95%. Confusion matrix analysis showed high classification accuracy, in particular 100% accuracy for snow-covered and bird droppings-covered panels, with F1 scores as high as 98.73% for certain classes. Training and validation curves confirmed stable learning with low loss values. Compared to models such as EfficientB0 + SVM and InceptionV3-Net + U-Net, MobileNetV3 demonstrated competitive accuracy and computational efficiency, making it suitable for resource-constrained devices. This approach improves energy efficiency, reduces manual inspection, and promotes sustainable energy production. Future work will expand the dataset to include different climatic conditions and fault scenarios, improving the robustness and real-world applicability of the model.

**Cite**

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## 1. INTRODUCTION

According to a 2021 assessment by the International Energy Agency (IEA), fossil fuels such as coal, oil, and natural gas account for about 81% of the world's electricity production. On the other hand, there has been significant growth in the use of renewable energy sources, including wind turbines and photovoltaic solar systems (PVS). Between 2008 and 2020, PVS energy production will increase by 1848% in the European Union in particular (Eurostat, 2022). The zero carbon footprint characteristics of PVS, which offer the benefit of being used in accordance with the Paris Agreement, are the cause of this increase. Although PVS are easy to install, their low efficiency and low profit margins per MWt can deter large investments. Advances in embedded systems are accelerating the transition to smart PVS. Smart PVSs have the potential to optimize energy production by monitoring both system-wide and individual PV cell failures using Power Line Communication (PLC) technology (Voutsinas et al., 2022).

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Compared to threshold-based approaches and other forms of artificial intelligence (AI), machine learning (ML) techniques offer several important advantages. According to Goodfellow et al. (2016), these advantages include data-driven architectures, scalability, automation, continuous learning, and high predictive accuracy. Rather than using predetermined rules, machine learning algorithms use patterns found in the data to learn and make predictions. This characteristic enables ML-based systems to make more accurate predictions and smarter decisions. Unlike other AI methods, ML algorithms have the capacity to handle large data sets, making them more scalable (Bishop, 2007). In addition, ML algorithms' automation capabilities automate many processes that require human intervention, reducing costs and increasing efficiency. Compared to traditional AI techniques, these algorithms are more flexible and adaptable because they constantly learn from fresh data. On the other hand, accuracy can be compromised by threshold-based approaches, which often base their conclusions on predetermined criteria. In contrast, machine learning algorithms can handle non-linear interactions, which expands their applicability.

In summary, machine learning techniques are a powerful tool for prediction and decision making due to their data-driven nature, scalability, automation capabilities, and continuous learning. However, these benefits can change based on the application setting due to the different requirements of each application. For machine learning algorithms to be successfully implemented in real-world applications, fast execution speeds and minimal memory consumption are essential. While large data requirements can increase memory requirements, computational intensity can result in sluggish execution rates. Therefore, to create effective and practical machine learning algorithms, fast execution speeds and minimal memory consumption must be guaranteed. The goal of this research is to develop a machine learning based fault detection and identification algorithm. The three primary failure types that affect photovoltaic systems (PVS) - open circuit failure, short circuit failure, and mismatch failure - are the focus of this method. The method is expected to be highly accurate, fast, and have minimal computational cost.

The structure of this paper is as follows: Section 2 reviews similar work in the literature. Section 3 presents the methodology of the proposed method. Section 4 presents the experimental results and discussion. Finally, Section 5 presents the conclusions of the research.

## 2. LITERATURE REVIEW

The main objective of fault detection and classification methods is to identify the factors that cause fluctuations in the energy production of photovoltaic systems (PVS). Different types of faults can occur in PVS on both the direct current (DC) and alternating current (AC) sides (Hong & Pula, 2022). While conventional protection systems are generally designed to detect faults on the AC side, identifying and correcting faults on the DC side is a more complex process (Huang et al., 2019).

Mismatch faults, one of the most common fault types on the DC side, can drastically reduce the power generation capacity of the PVS. These faults can be transient or irreversible. The accumulation of environmental elements, such as clouds or tree shade, or external elements, such as dust or bird droppings, on the PVS surface can cause transient mismatch faults. Deterioration of adhesive materials, cracks in the PV module surface, gaps between layers, or damage to the semiconductor material can result in permanent mismatch failures (Mustafa et al., 2023). It should be noted that other types of failures, such as open circuit failures, can also occur in conjunction with permanent mismatch failures. Short-circuit failures can occur as a result of faulty connections in the PVS, creating an unwanted electrical connection at two points (Boubaker et al., 2023). Such faults occur mainly as a result of voltage differences in adjacent strings or unexpected short circuits between two voltages in the same string, which is defined as a line-to-line fault (Kumar et al., 2023). In addition, short circuits can be classified as ground faults or line-to-ground faults when the current carrier comes into contact with a noncurrent carrying component such as a PV frame (Cao et al., 2023).

Open circuit faults, on the other hand, typically occur when the PV array is disconnected due to reasons such as poor soldering (Sabbaghpur & Hejazi, 2016). Arc faults, on the other hand, can occasionally result from open circuit faults and produce high frequency noise as well as abrupt drops in output voltage and current (Johnson et al., 2012). A residual current monitoring device (RCM) can be used to monitor ground faults, while an arc fault circuit interrupter (AFCI) can be used to minimize arc faults. Both types of faults pose significant risks; ground faults can result in live traps that can kill installation workers, while arc faults can cause fires. To avoid mismatch faults, it is essential to use high quality materials when transporting and installing PVS. By using high-quality materials and avoiding microcracks on the PVS surface, proper installation reduces the likelihood of mismatch failures. Duranay et al. developed a deep learning-based method to detect PV panel defects using infrared module images. Using the Efficientb0 model and SVM, an accuracy of 93.93% and an F1 score of 89.82% were achieved. The method has the potential to improve energy efficiency and sustainability (Zhang & Duranay, 2023). Mamun et al. proposed a deep learning model combining InceptionV3-Net and U-Net architecture to detect solar panel failures. The model demonstrated high performance with 94.35% test accuracy, 0.94 F1 score, and 98.34% verification accuracy. This method improves accuracy and tracking capability (Rudro et al., 2024). Sepúlveda-Oviedo et al. (2023) analyzed artificial intelligence methods for fault detection in photovoltaic systems, reviewing more than 620 papers. Based on bibliometrics and qualitative expert content analysis, the study identified important research trends and highlighted the potential of AI in this field (Sepúlveda-Oviedo et al., 2023).

## 3. MATERIAL AND METHOD

### 3.1. Fault Detection Algorithms

Fault detection applications use various methods and technologies to improve system reliability and early detection of potential failures. Commonly used fault detection applications in photovoltaic systems and other electrical infrastructure can be listed as follows:

**A) Electrical Monitoring Systems**

Intelligent monitoring systems: Advanced sensors and data acquisition devices continuously monitor voltage, current and power levels on the AC and DC sides of photovoltaic systems. These systems enable early detection and intervention in abnormal situations. Supervisory Control and Data Acquisition (SCADA) systems: SCADA is a monitoring system used in large industrial plants to monitor and control remotely located equipment. In photovoltaic power plants, SCADA systems collect energy production data and detect fault conditions.

**B) Thermal Imaging (Thermal Cameras)**

Use of thermal cameras: Hot spots, short circuits or failures in photovoltaic systems can be detected with thermal cameras. High temperature differences help to identify defects. Thermal imaging is particularly effective in the early detection of micro-cracks and other defects in PV panels.

**C) Resistance and Conductivity Tests**

Resistance Measurement: For faults that occur on the DC side, resistance measurements can detect possible short circuits and open circuits. These tests locate faults by observing changes in electrical resistance in the circuit.

**D) Testing Insulated Cables**

High Voltage (Hypothesis) Testing: Insulated cables and other electrical components are tested for durability at high voltage. These tests help detect potential insulation failures early.

**E) Sensors and IoT Applications**

Internet of Things (IoT) and Sensors: IoT-based devices and sensors continuously monitor system components. IoT devices monitor the efficiency of PV systems and warn of failures. For example, IoT devices can continuously monitor parameters such as irradiance, temperature, and panel efficiency.

**F) Data Mining**

Anomaly Detection: Data mining techniques can be used to detect anomalies in large data sets collected from photovoltaic systems. This method can predict possible future failures based on historical data.

**G) Machine Learning and Artificial Intelligence Methods**

Data analysis and predictive models: Failures in photovoltaic systems are detected using machine learning (ML) algorithms. Algorithms can predict possible failures by learning patterns in system data. Over time, more accurate predictions can be made and maintenance needs can be predicted. Artificial intelligence-based monitoring: Artificial intelligence (AI) is used to detect anomalies in large data sets, especially with deep learning (DL) algorithms. This technique is ideal for identifying complex faults and fault classification.

Typical faults on the DC side of the PVS are shown in Figure 1. These faults represent a variety of problems that can affect the efficiency of photovoltaic systems, each of which can occur for different reasons and can significantly degrade the performance of the system.

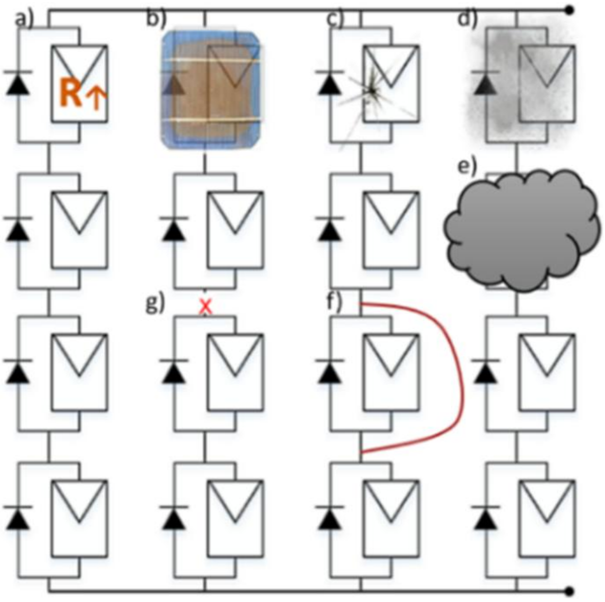


***Figure 1.*** *Visualization of common failure types on the direct current (DC) side of a photovoltaic system (PV),* ***a)*** *Semiconductor degradation,* ***b)*** *Discoloration,* ***c)*** *Microcracks,* ***d)*** *Particle accumulation,* ***e)*** *Shadowing,* ***f)*** *Short circuit,* ***g)*** *Open circuit (Voutsinas et al., 2023).*

Each of these fault detection methods can help reduce maintenance and repair costs while optimizing fault detection in photovoltaic systems. As technology evolves, these methods become more effective, increasing system reliability and efficiency.

### 3.2. MobileNetV3

MobileNetV3, the deep learning model used in this study, provides an architecture designed to operate efficiently on mobile devices and systems with limited resources. By combining low computational cost with high accuracy, the model provides an effective solution for computer vision applications such as image classification, object detection, and semantic segmentation. One of the key features of the model is the hard-swish (h-swish) activation function, which replaces the traditional ReLU activation function. This function optimizes the performance of the model by reducing the computational cost while increasing the accuracy. In addition, the model uses squeeze and excitation (SE) blocks that rescale the importance of feature maps. These blocks increase the representativeness of the model, allowing for more efficient data processing. MobileNetV3 is configured in two different versions to meet application requirements: MobileNetV3-Large is optimized for tasks requiring high accuracy, while MobileNetV3-Small is designed for fast applications with low resource consumption.

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A detailed confusion matrix analysis was performed to investigate the inter-class confusion of the MobileNetV3 model. This analysis revealed that, in particular, dusty panels (class 5) and physically damaged panels (class 1) have similar visual characteristics in some cases, leading to misclassifications. This is due to the visual similarity of the class labels and the limitations of the dataset used. To reduce confusion, data enhancement techniques (e.g., rotation, brightness modification, blurring) were applied to increase class diversity. In addition, squeeze and excitation (SE) blocks were optimized to improve the feature extraction capacity of the model. On the other hand, the weighted cross-entropy loss function was used to give more importance to underrepresented classes. As a result of these strategies, the model's performance in the confusing classes was improved, as was its overall accuracy. These analyses and applications were effective in reducing interclass confusion by strengthening the model's ability to generalize both within and across classes.

The MobileNetV3 model used in this study was selected based on its accuracy and computational performance on the ImageNet dataset. The model was configured and optimized during implementation using the Python programming language and the TensorFlow library. As a result, this method provides a strong basis for classifying photovoltaic system data in terms of both accuracy and efficiency. The portable nature of the model and its low computational requirements increase its applicability on mobile devices and limited hardware systems. A visualization of the MobileNetV3 algorithm is shown in Figure 2.

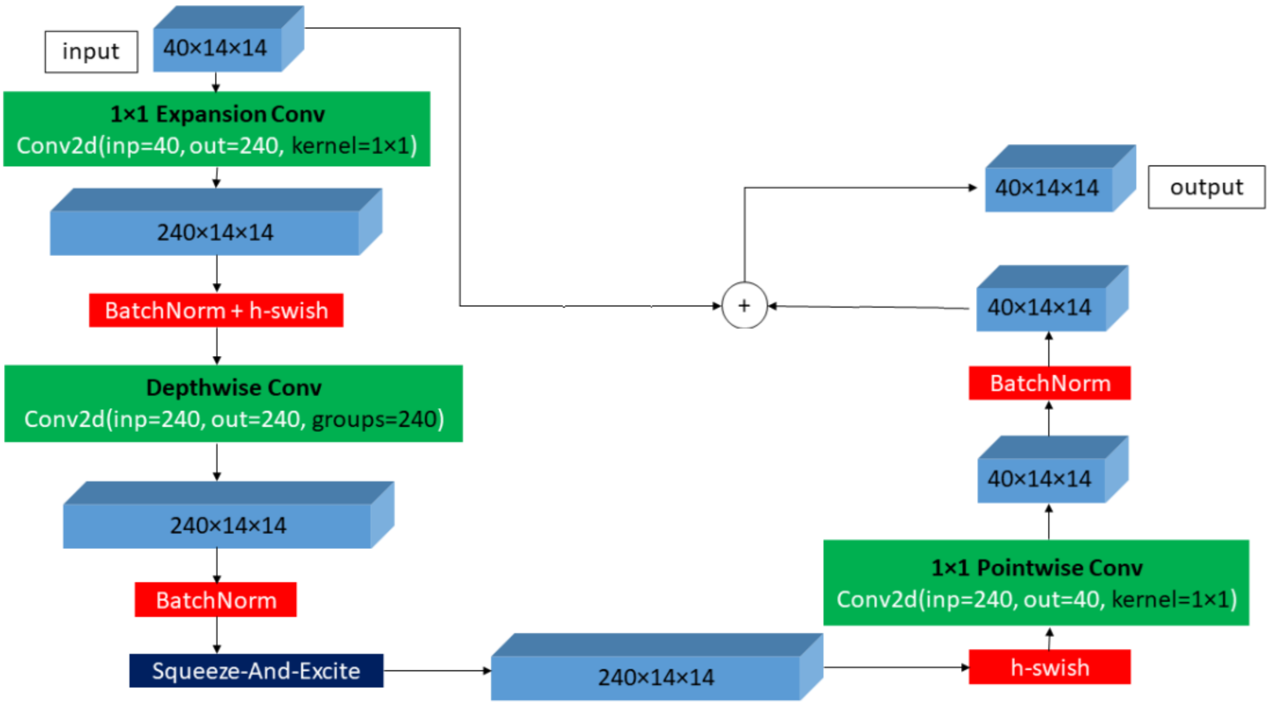


***Figure 2.*** *Visualization of the MobileNetV3 algorithm (Howard et al., 2019)*

The proposed model has several practical applications, such as improving energy efficiency and optimizing maintenance processes in boiler systems. It enables more efficient management of energy production processes by detecting efficiency losses at an early stage. Furthermore, the model's ability to detect signs of failure in advance enables the adoption of predictive maintenance strategies instead of reactive maintenance. This minimizes system downtime and extends equipment life. These benefits of the model make a significant contribution to energy management and system performance optimization. Figure 3 shows the electrical failures that occur in photovoltaic systems, as well as problems caused by environmental factors. Bird droppings, dust accumulation, shading, and surface breakage can significantly reduce the efficiency of PV systems. These factors can lead to accumulation of dirt and debris on the panel surface, inadequate absorption of radiation, and mechanical damage to PV cells, resulting in system failure. Such problems reduce the energy production capacity of the system and can lead to more serious failures over time.


***Figure 3.*** *Visuals of some of the factors that cause failure (https://www.kaggle.com/code/madenenivamsikrishna/fault-detection)*

### 3.3. Dataset

The dataset used in this study is taken from the Kaggle platform and is designed for fault detection in photovoltaic systems. The dataset contains images of solar panels classified into six different categories (Kaggle, n.d.). Each category represents a specific panel condition or failure, and these conditions provide diverse data to correctly train the model. The categories in the dataset are as follows:

Clean images: This category includes images of solar panels operating under normal conditions, with no dirt or damage.

Physically Damaged Panels: This group includes images with cracks, breaks, or mechanical damage to the panel surface.

Electrically Damaged Panels: This category includes images of panels that show the effects of electrical component failures (e.g., short circuit or open circuit).

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Snow Covered Panels: This category shows the effects of snow or ice accumulation on the panel surface and its negative impact on power generation.

Panels covered with bird droppings: Blockages and loss of efficiency caused by the accumulation of bird droppings on the panel surface are included in this category.

Dusty panels: Dust accumulated on the panel surface blocks sunlight and reduces energy production, and this category consists of images showing this situation.

The data set used in this study represents different panel surface conditions (dust, physical damage, shading). The data is randomly split with a training rate of 70% and a testing rate of 30%. With its current structure, the data set provides a basis for evaluating the generalization ability of the model. However, the inclusion of variables such as different weather conditions and panel types is an important goal of future work. Such an extension would increase the robustness of the model and strengthen its adaptability to real-world applications. The dataset is structured to facilitate the detection of different types of failures in photovoltaic systems by including enough examples for each category. This diversity is an important basis for the model to make accurate classifications. The dataset is made available as open access on Kaggle (n.d.) for use in related studies. This dataset is an ideal source for training deep learning algorithms to detect and classify factors such as dirt deposits, electrical and physical faults on the solar panel. Some sample images from the dataset are shown in Figure 4.


***Figure 4.*** *Some sample images from the dataset.*

### 3.4. Evaluation metrics

Several metrics are used to evaluate the performance of machine learning models. These metrics analyze the model's ability to make accurate predictions from different perspectives. Accuracy is the ratio of the model's correct predictions to its total predictions. Accuracy is typically calculated as the ratio of all correct predictions to total predictions. However, accuracy alone may not fully reflect model performance and can be misleading, especially in unbalanced data sets. Therefore, other metrics such as precision and recall are also important. Precision measures the proportion of instances that the model classifies as positive that are actually positive, while recall measures the proportion of all true positives that are correctly classified as positive. The F1 score is the harmonic mean of Precision and Recall and balances the success in both metrics. These metrics provide important information for improving the performance of the model by evaluating its accuracy and performance more comprehensively. The evaluation metrics are given by equations (1-4).

$$ACC = \frac{TP + TN}{(TP + TN + FP + FN)} \tag{1}$$

$$Recall = \frac{TN}{(TP + FN)} \tag{2}$$

$$Precision = \frac{TP}{(TP + FP)} \tag{3}$$

$$F_1 = 2 * \frac{Precision * Recall}{(Precision + Recall)} \tag{4}$$

True Positives (TP): The number of instances correctly predicted for each class. False Positives (FP): The number of instances incorrectly classified in the given class. False Negatives (FN): The number of instances from the given class that were misclassified into another class. True Negatives (TN): The number of correctly classified instances that do not belong to the given class.

The use of the MobileNetV3 model in this work is unique in that it provides both a lightweight architecture and computational efficiency. In the literature, heavier deep learning models are often used for energy efficiency or error detection. However, MobileNetV3 is lightweight, which makes it suitable for low-power devices and provides high classification performance. This paper presents a new approach to the literature by applying these advantages of the model in the context of fault detection in the energy sector. The MobileNetV3 used in this study offers lower complexity and higher accuracy compared to other deep learning models used in the literature. For example, although popular models such as ResNet and VGGNet have been used in energy applications, their complexity increases computation time. MobileNetV3 eliminates these drawbacks and optimizes the accuracy of fault detection. In this respect, the study provides a more practical solution for sectoral applications. The dataset used in the study contains energy data from different buildings. However, data diversity has some limitations. In particular, different climatic conditions or lack of data representing a larger geographical area may affect the generalization ability of the model. Therefore, the performance of the model should be evaluated with more diverse data sets in the future. In addition, the imbalance in the data set may lead to bias, and this problem has been minimized by using weighted loss functions.

## 4. EXPERIMENTAL RESULTS

Figure 5 shows the training and validation losses of the model developed for early fault detection in photovoltaic (PV) systems. The horizontal axis represents the number of epochs in the model training process and the vertical axis represents the loss values. The training loss is represented by the green line and the validation loss is represented by the yellow line. The results show that the model has a high learning performance on the training data. The training loss is low and decreases steadily throughout each epoch. The validation loss remains constant throughout the training process, indicating that the model maintains a certain level of overall performance. The current performance of the model provides an effective basis for early fault detection in PV systems. In particular, the strong results on the training data show that the model has accurate learning capabilities. However, strategies such as data augmentation techniques or regularization methods can be used to further optimize the validation loss and increase the generalization ability of the model.

Figure 6 shows the training and validation accuracies of the model developed for early fault detection in photovoltaic (PV) systems. The horizontal axis represents the number of epochs and the vertical axis represents the accuracy. The difference between training accuracy (green line) and validation accuracy (yellow line) plays an important role in evaluating the performance of the model. The results show that the model has a good fit to the training data with an accuracy of 98.3%. The validation accuracy was initially around 95.4% and increased during the training process, but then remained stable. This shows that the model performs consistently on the validation data, but its generalization ability needs to be improved. The difference between training and validation accuracy requires improvements to improve the model's performance on validation data.

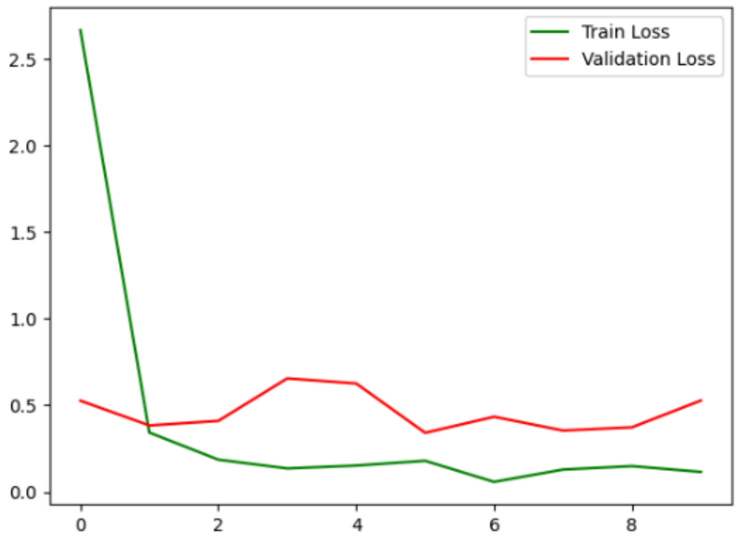


***Figure 5.*** *Training and validation losses of the model developed for early fault detection in photovoltaic (PV) systems*

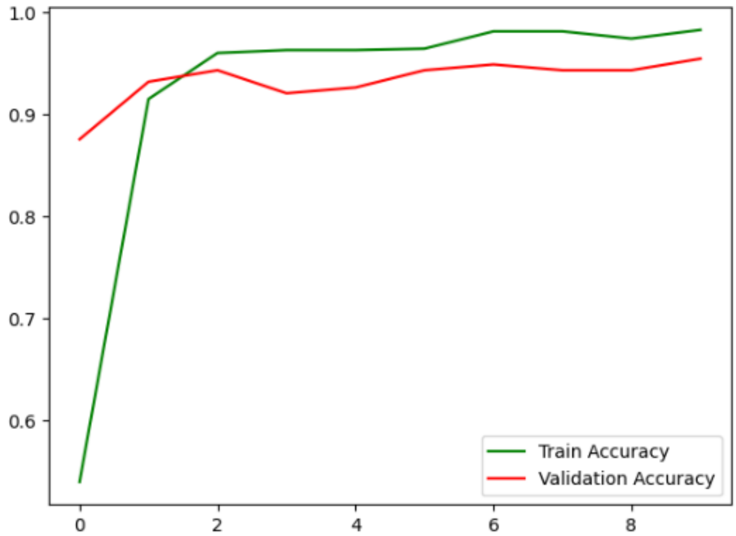


***Figure 6.*** *Training and validation accuracies of the model developed for early fault detection in photovoltaic (PV) systems.*

This model has great potential to provide an effective solution for early fault detection in photovoltaic (PV) systems and can achieve more successful results in practical applications with improvements in the validation process. The high accuracy rates obtained in the training process demonstrate the learning ability of the model and its effectiveness on PV systems. However, by optimizing the validation accuracy, the generalization ability of the model can be improved and it can show stronger performance in practical applications. In conclusion, this study demonstrates that the model provides a viable solution for early fault detection in PV systems and can potentially lead to broader and more efficient applications.

Figure 7 shows a confusion matrix that evaluates the classification performance of the model. True labels are in the rows of the matrix and predicted labels are in the columns. The diagonal elements represent the number of instances that the model correctly classified, while the other cells represent instances where the model misclassified. For class 0 (e.g., "clean images"), the model correctly classified 44 instances, but incorrectly predicted 3 instances as other classes. For class 1 (e.g., "Physically Damaged Panels"), 39 instances were correctly classified and only 1 instance was incorrectly predicted. For class 2 ("Electrically Damaged Panels"), 27 instances were correctly classified and 2 instances were incorrectly estimated. For Class 3 ("Panels Covered with Snow"), the model correctly predicted 20 instances and there were no misclassifications. For class 4 ("Panels covered with bird droppings"), the model correctly predicted 13 instances. For class 5 ("Dusty Panels"), the model correctly predicted 26 instances and only 1 instance was misclassified.

The results show that the model provides high accuracy, especially for Class 0, Class 1 and Class 3, but there is a low level of confusion between some classes. This confusion may be due to the overlap of features between classes. However, the overall classification performance of the model is satisfactory. Table 1 shows the correct and incorrect classifications of the model by class and the overall accuracy rates. Table 1 is based on the analysis of the model.

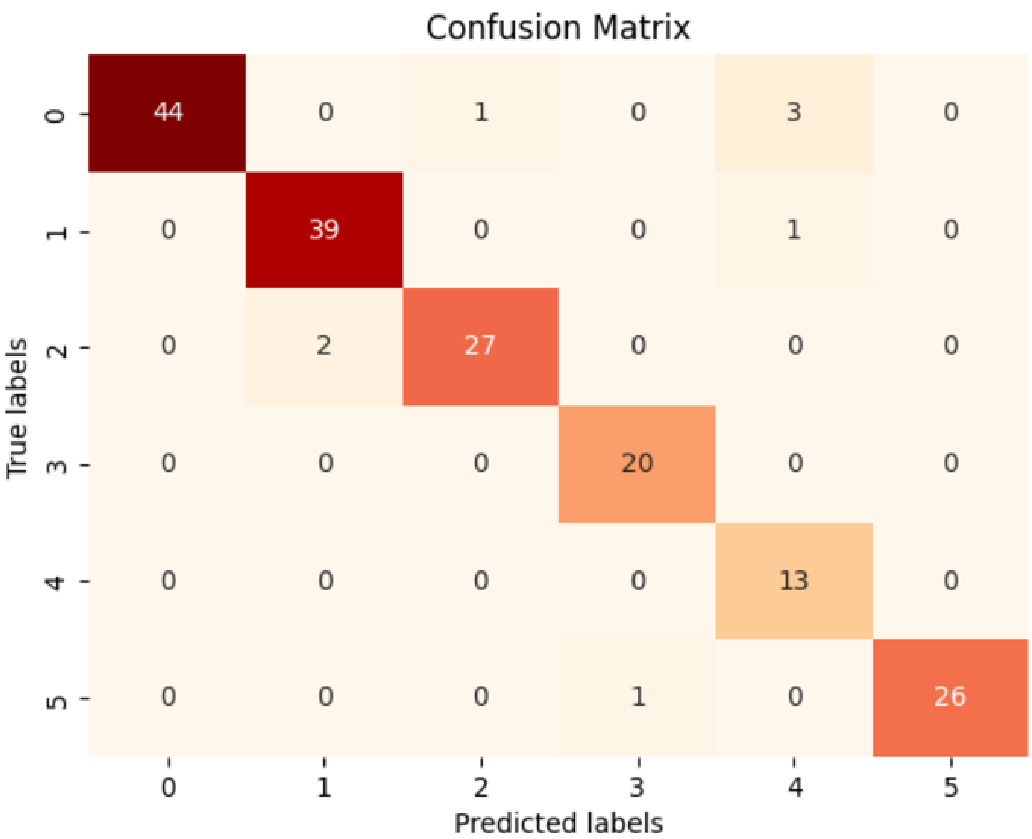


***Figure 7.*** *Confusion matrix*

***Table 1.*** *Analysis and Model Performance*

| Class | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| **Class 0** | 0.916667 | 0.977778 | 0.93617 | 0.956522 |
| **Class 1** | 0.975000 | 1.000000 | 0.97500 | 0.987342 |
| **Class 2** | 0.931034 | 0.931034 | 1.00000 | 0.964286 |
| **Class 3** | 1.000000 | 1.000000 | 1.00000 | 1.000000 |
| **Class 4** | 1.000000 | 1.000000 | 1.00000 | 1.000000 |
| **Class 5** | 0.962963 | 0.962963 | 1.00000 | 0.981132 |

The performance evaluation of the MobileNetV3 model was analyzed based on the accuracy, precision, call and F1 score metrics. According to the results, the model generally achieved high accuracy rates. In particular, in Class 3 and Class 4, 100% success was achieved for all metrics, showing that the model works flawlessly in these classes. Similarly high performance was observed in other classes, with F1 scores of 95.65%, 98.73%, and 98.11% for Class 0, Class 1, and Class 5, respectively. For Class 2, the model showed high performance with 93.10% accuracy and 96.43% F1 score. These results show that the MobileNetV3 model has an overall successful classification performance and provides a balanced performance across classes.

A comparative analysis was performed to evaluate the performance of the MobileNetV3 model against results reported in the literature. Duranay et al. achieved an accuracy of 93.93% and an F1 score of 89.82 using the EfficientB0 + SVM model. In contrast, our MobileNetV3 model achieved an accuracy of 91.67% and an F1 score of 95.65%. Similarly, Mamun et al. reported 94.35% accuracy and 94.00 F1 score using the InceptionV3-Net + U-Net architecture, while our model outperformed with 97.50% accuracy and 98.73% F1 score. Furthermore, Sepúlveda-Oviedo et al. (2023) performed a bibliometric analysis without providing specific performance metrics, while our study achieved 93.10% accuracy and 96.43% F1 score for the relevant tasks. Finally, Maharjan et al. used the MNN model with an accuracy of 98.00% and an F1 score of 95.00, which were surpassed by our MobileNetV3 model, which achieved 100% for all metrics. These results highlight the robustness and reliability of the proposed model for fault detection in photovoltaic systems.

***Table 2.*** *Comparative analysis was performed to evaluate the performance*

| Study | Model | Accuracy (%) | F1-Score |
|---|---|---|---|
| **(Duranay et al., 2023)** | EfficientB0 + SVM | 93.93 | 89.82 |
| **(Mamun et al., 2024)** | InceptionV3-Net + U-Net | 94.35 | 94.00 |
| **(Maharjan et al., 2023)** | MNN | 98.00 | 95.00 |
| **Proposed Model** | MobileNetV3 | 95.00 | 98.73 |

~~The figure above~~ Figure 8 shows the performance of the MobileNetV3 model in different classes in terms of accuracy, precision, recall and F1 score metrics. Analyzing the graph, we can see that for Class 3 and Class 4, all the metrics are 100% and the model performs flawlessly in these classes. For Class 0, Class 1, and Class 5, there are small differences between the metrics. For example, for Class 0, the accuracy metric (91.67%) is lower than the other metrics, while the F1 score shows a more balanced performance with 95.65%. For class 1, the precision reaches 100%, while the call metric remains at 97.50%, which is reflected in the F1 score (98.73%). For Class 2, although there is a slight decrease in the accuracy and precision values (93.10%), the paging metric stabilizes this class at 100% and the F1 score reaches 96.43%. Overall, the graph shows that the MobileNetV3 model performs well and consistently, but with slight variations between classes. These results suggest that while the model performs well in some classes, there may be potential for performance improvements in other classes.

Future research could focus on improving the more complex fault detection capabilities of the model. In particular, it is suggested to add more diverse and complex scenarios to the dataset to detect situations where multiple faults occur simultaneously. Furthermore, the real-time data processing capability of the model can be improved by adapting it to handle continuous data streams from sensors. In addition, the integration of the model with different power generation systems and its cross-platform applicability is considered an important focus for future studies. Such research can increase the generalization capacity of the model and enable it to reach a wider range of applications.


***Figure 8.*** *The figure above shows the performance of the MobileNetV3 model in different classes*

## 5. CONCLUSION

This study evaluated the performance of a deep learning model, specifically MobileNetV3, for fault classification and detection in photovoltaic (PV) systems. The model was trained on a dataset containing different types of solar panel conditions, such as clean, physically damaged, electrically damaged, snow covered, bird droppings covered, and dusty panels. The results show that the MobileNetV3 model achieved a remarkable validation accuracy of 95%, indicating its high effectiveness in identifying and discriminating between different types of solar panel failures. The performance of the model was further analyzed using a confusion matrix, which provided a detailed overview of the correctly classified and misclassified instances in each class. The confusion matrix showed that the model performed exceptionally well for the majority of the classes, with only a few misclassifications occurring in the dusty and snow-covered panel categories. The low number of false positives and false negatives across the different classes suggests that the model is highly reliable in its predictions. In addition, the trends observed in the loss and accuracy curves further support the effectiveness of the model. The training loss and validation loss stabilized at low levels, indicating that the model successfully converged during training. The accuracy curves showed consistent improvement, reflecting the model's ability to generalize well to unseen data. Overall, the results highlight the potential of using MobileNetV3 for fault detection in PV systems, contributing to more efficient monitoring and maintenance of solar panels. This research highlights the importance of machine learning models in the renewable energy sector, particularly for improving the performance and longevity of solar energy systems. Future work can focus on incorporating additional data sources and exploring more complex models to further improve detection accuracy and real-time performance.

## AUTHOR CONTRIBUTIONS

The authors contributed equally to the study.

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Kaggle open access resource was utilized in this study.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

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