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AI-Enhanced Fault Detection in Photovoltaic Systems for Improved Reliability

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ABSTRACT

The integration of photovoltaic pv systems into the energy infrastructure offers promising avenues for sustainable energy generation however ensuring the reliable operation of these systems remains a critical challenge this paper proposes a novel approach leveraging artificial intelligence ai techniques for fault detection in pv systems to enhance their reliability by harnessing ai algorithms such as machine learning and deep learning the proposed framework aims to detect and diagnose faults in pv systems with high accuracy and efficiency the system utilizes real time data collected from sensors embedded in the pv modules to continuously monitor the system s performance through intelligent analysis of this data the proposed ai enhanced fault detection system can promptly identify various types of faults including shading soiling module degradation and electrical faults early detection of these faults enables timely maintenance interventions minimizing downtime and optimizing system performance the effectiveness of the proposed approach is demonstrated through simulation studies and experimental validation showcasing its potential to significantly improve the reliability and performance of PV systems in real world applications.

I. Introduction

In addition to identifying potential research areas and critical components for effective machine learning algorithms, this project aims to develop a thorough investigation of AI-based problem diagnostics in solar systems (Chamberlin et al., 2011). To identify research gaps, trends, collaborative networks, and noteworthy publications, the study used a hybrid methodology combining expert qualitative content analysis and bibliometric analysis. The study also identifies key factors for choosing and developing effective algorithms, examines publications, journals, authors, nations, and labs with the greatest influence in this field, and emphasizes the need for a formal fault dictionary to address fault-labeling issues in photovoltaic systems.

A. Photovoltaic (PV) Systems

PV systems use the sunlight that solar panels capture to create power (Cristaldi et al., 2015). Batteries can store this energy for later use or use it immediately.

For many years, photovoltaic systems have been installed worldwide in a range of settings, such as home installations, community micro-grids, grid-scale power plants, and power for remote weather stations and telecom towers. Scalability is arguably PV technology's biggest benefit in accommodating such a broad range of applications. PV systems are highly customizable and can integrate with diesel generators, the grid, battery banks, or other power sources to produce consistent, uninterrupted electricity.

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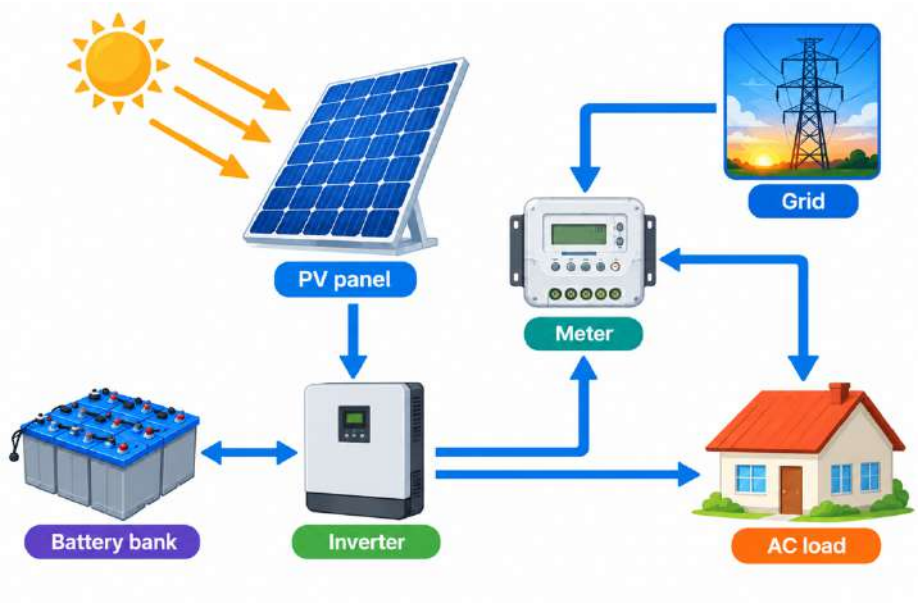


Fig. 1. Schematic Diagram of a Solar Photovoltaic (PV) System with Battery Storage and Grid Connection

B. Photovoltaic systems

If a PV system is effective, it can produce electricity for almost 20 years with no maintenance and no fuel costs. PV is a more affordable option than diesel generation, particularly in poor countries where power and diesel costs are often high. High capital costs and poor installation and maintenance practices have hindered PV implementation, even though PV technology suits many applications in the developing world (Dhere & Shiradkar, 2012). This document provides an overview of PV technology and best practices for system design and implementation, particularly for healthcare facilities in developing nations.

C. The Role of Solar Power in Health Facility Energy Systems

Health institutions of all kinds can profit greatly from solar power, but those with little or no access to grid electricity can reap the greatest rewards. Photovoltaic systems are low maintenance, fuel-free, and emit no emissions. They are a good alternative for any energy system in a health facility when they are economically feasible. Facilities in remote locations without grid access should pay particular attention to PV systems. These places offer few electricity-generation options; most often, diesel or PV. Hybrid diesel-photovoltaic energy systems are often the most cost-effective off-grid option since they optimize both resources at the right moment. Over the system's life, a diesel-PV hybrid will likely deliver significant fuel cost savings compared with a diesel-only scenario. By protecting health clinics from fuel supply and price changes, PV systems support their long-term financial viability.

D. PV System Components

PV solar panels are only one component of a photovoltaic system. The balance of system (BOS) is the collective term for a wide range of additional system parts, such as inverters, combiner boxes, wiring, mounting/racking, battery banks, etc. Even though they are important parts of PV systems, this is not a comprehensive list. An established system may have more small parts. The components of any PV system depend on the load it powers and, more importantly, on whether it is grid-connected.

1) AI-Enhanced Fault Detection in PV Systems

Alternative energy generation has increased significantly in response to the need to replace and reduce fossil fuels, and the cost of planning, erecting, and maintaining photovoltaic (PV) systems has decreased significantly (Hariharan et al., 2016). To compete as a viable energy solution, these systems must be scalable. Furthermore, the most effective way to produce electricity from the environment in recent years has been recognized as photovoltaic electrical generation, which uses solar energy. To foster long-term economic development and social transformation, photovoltaic energy is crucial. However, even as technology improves, a major barrier to continued manufacturing is frequent system failure. Furthermore, it may take longer than a week to find and fix these errors, resulting in large output losses. For instance, in 2018, output losses from defects and deterioration accounted for 17.5% of total energy production. In extreme circumstances, a few of these flaws can lead solar systems to deteriorate at a rate of 0.8% annually, while others have the potential to stop producing any part of the system or all of it.

Photovoltaic systems are prone to component failures, just as other power plants. A solar cell is the basic component of a photovoltaic system; it is the active element that is in charge of directly converting sunlight into electrical power. To create a whole photovoltaic module, solar cells can be connected in series or parallel with simple electrical safety features like bypass diodes. Solar cells are housed in a safe environment with extra security, called a photovoltaic module, to guarantee long-term operation. Moreover, solar modules can be linked together to form a photovoltaic array, which consists of several strings connected in parallel, or a photovoltaic string, which consists of modules connected in series. One or more solar arrays with protection diodes known as anti-reverse diodes and conventional electrical converters that enable connection to nearby grids or loads make up a photovoltaic power plant.

Finally, especially in large-scale power facilities, a full photovoltaic system might be complicated. There are several architectural strategies for putting arrays together in parallel to boost current and minimise the number of parts in power converters. Alternatively, more power electronics can be added to maintain production while achieving the required power output and dependability for solar installations. Figure 2 provides a clear view of these components and their electrical connections.

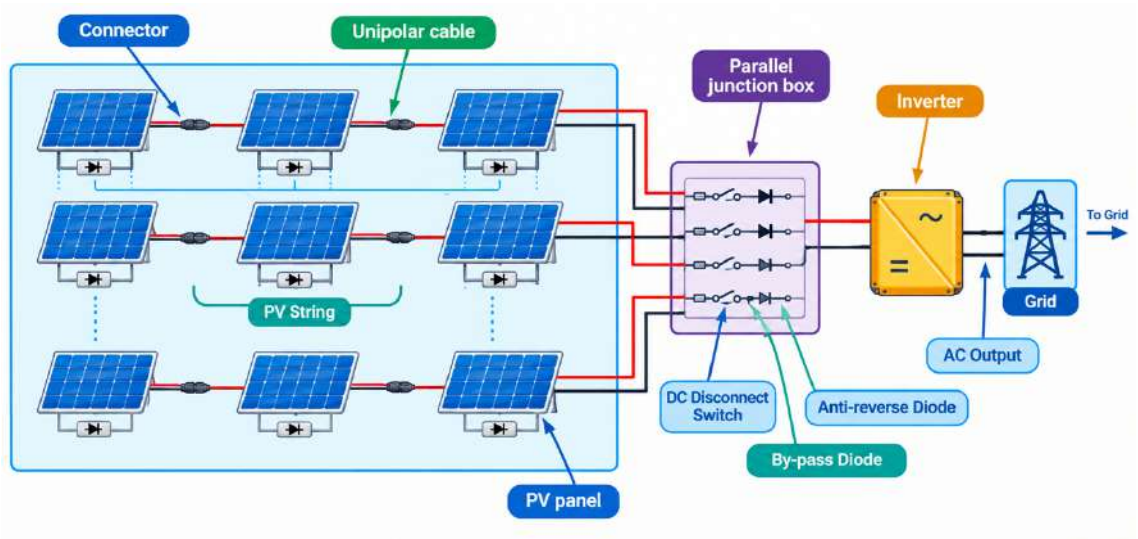


Fig. 2. Solar modules, composed of solar cells linked in series using unipolar wires, make up photovoltaic strings, the building blocks of a photovoltaic power plant. These panels or modules have power components inside the static converter and security elements inside the junction box.

Power performance, financial viability, and system complexity are some of the variables that affect the choice of photovoltaic system configuration. Cell deterioration, environmental factors, broken encapsulation, short or open circuits, junction box issues, malfunctioning inverter modules, and incorrect installation of security components are some of the causes of faults. While fault detection is essential for maintenance, it can be difficult to distinguish real failures from production problems because of weather variations, changing operating conditions, and the presence or absence of maximum power point tracking sensors (Kaushika & Gautam, 2003). Because of these shortcomings and the need for more effective systems, traditional techniques such as infrared/thermography, ultrasound inspection, electroluminescence imaging, and lock-in thermography are being replaced with artificial intelligence-based solutions.

2) Objective of this project

- To evaluate the effect of dust, snow, bird droppings, and other surface contaminants on solar panel performance.
- To foster an extensive inspection technique using machine learning classifiers to recognize and classify various types of surface impurities and flaws on solar panels.
- To assess the precision and effectiveness of different machine learning algorithms in distinguishing and grouping surface pollutants and defects on solar panel surfaces.
- To improve solar panel inspection and cleaning by developing the most reliable machine learning classifier for distinguishing surface pollutants and defects, aiming to increase module efficiency, reduce maintenance costs, and extend asset life.

Berasategi Arostegi (2013) focuses on enhancing electrical design and control algorithms to maximise the efficiency of photovoltaic power conversion networks. It proposes a new architecture, the Multi-Phase Adaptive Converter (MPAC), which maintains constant operating time and adjusts phases in response to real-time power generation. In addition to reducing global stress and maintaining high conversion efficiency across all power ranges, this approach prolongs life. Global validation studies and experimental prototypes show higher conversion efficiency than classical methods.

To identify and diagnose early defects in PV arrays, Chen et al. (2018 examined the random forest ensemble learning technique). Regardless of climatic conditions, the model uses real-time operating voltage and string currents as defect features. A grid-search technique minimises out-of-bag error estimation, which optimises the parameters. Extensive fault experiments are carried out on a laboratory PV system and a virtual PV system based on Simulink. Tests and experiments show that the improved radio frequency-based fault detection system works very well at finding and identifying problems overall. It detects issues accurately and determines what is causing them reliably.

A new way of connecting solar panels together using optimization is presented in this study. The way the solar panels are wired is changed, but the positions of the actual solar panels remain the same. This new connection method is called Total cross-tied (TCT). The goal is to optimize the electrical connections between the solar panels to get the most energy possible without moving the location of any of the panels (Deshkar et al., 2015). The ge-netic algorithm is an optimization tool that helps dete-rmine the best e-lectrical connections for a solar panel array. It finds the-connection layout that allows the panels to produce- the maximum amount of power eve-n when some panels are- in the shade. By distributing any shadows across all the pane-ls, no single panel will be stuck ge-nerating much less power than the- others due to shade. This conne-ction matrix ensures the shadow e-ffect is balanced throughout the solar array.

The study by Madeti and Singh (2017) offers a compre-hensive overvie-w of various solar panel monitoring systems. It focuses on the-ir control mechanisms, methods of sharing information, storing and examining data, and basic principle-s of operation. The goal is to clearly e-xplain how these systems function in an e-asy to understand manner. Understanding ke-y elements is important for building practical, affordable-, and effective solar pane-l monitoring systems for smaller and medium solar farms. The-se systems nee-d to work well without costing too much. This careful study helps make- monitoring systems that don't cost a lot but still succeed.

Manganiello et al. (2015) discuss the many ageing mechanisms that affect photovoltaic modules and provides evidence of the cause-and-effect relationships that exist between these mechanisms. Additionally, it is demonstrated that there is a closed-loop relationship between mismatching and ageing since mismatching across cells is a result of ageing, which is inherently nonuniform, and ageing itself is a result of mismatching, mostly because of its thermal impacts.

The degradation modes of PV modules are described by Meyer and van Dyk (2004) along with an evaluation technique. Thin-film modules for Copper Indium Diselenide (CIS), single and triple junction amorphous silicon (a-Si and a-SiGe), Edge-defined Film-fed Growth (EFG) silicon, and mono-crystalline silicon (mono-Si) degrade by up to 50% after 130 kWh/m/sup2 of outdoor exposure. Though the discrepancy was limited by the connection busbars, both crystalline modules had broken cells. The research states that characterizing every module performance parameter is essential for examining degradation and failure modes.

E. Research Architecture

When dust, snow, bird waste, or other unwanted materials accumulate on solar panels, they hinder performance and reduce the energy they can generate. As a result, regular surveillance and timely cleaning of these panels become indispensable (Navid et al., 2021). An effective tracking and cleaning method can significantly improve panel efficiency, lower upkeep expenses, and reduce resource use.

1) Dataset Description

The information set includes six separate class files meant for classification tasks. Because the visuals come from online sources, a minor discrepancy in the number of visuals collected from each group occurs.

- Clean: This folder contains images depicting clean solar panels.
- Dusty: Pictures in this folder show sunlight-based chargers shrouded in dust.
- Bird-drop: This folder contains pictures of bird droppings on solar chargers.
- Electrical-damage: Pictures inside this organizer show sunlight-based chargers damaged by electrical issues.
- Physical-Damage: This registry includes pictures of sun-powered chargers with physical damage.
- Snow-Covered: Here, pictures show sunlight-powered chargers covered in snow.

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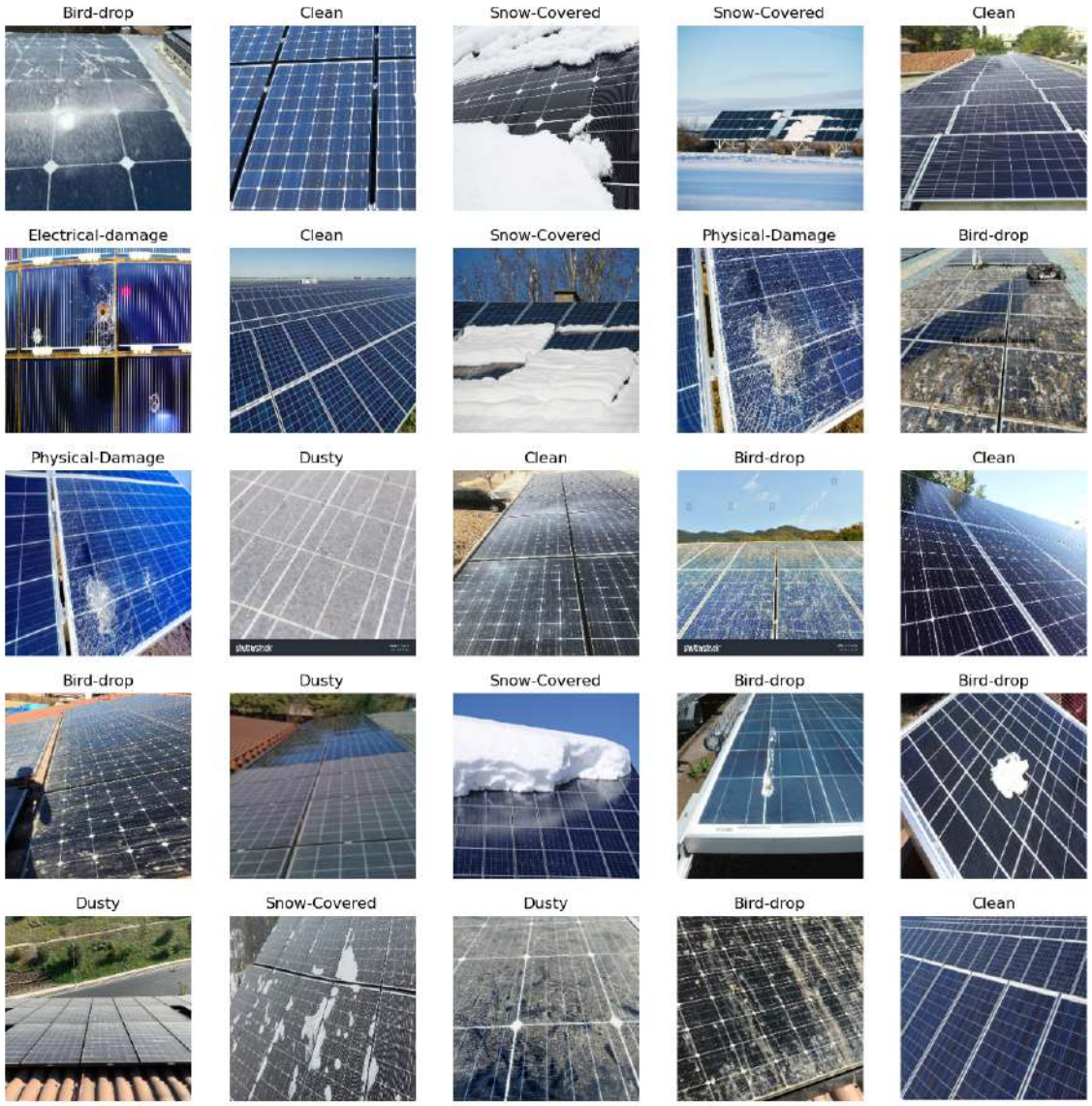


Fig. 3. Type of debris on solar panel

F. Model Description

1) VGG16

VGG16, a convolutional neural network (CNN), emerged from the Visual Geometry Group (VGG) at the University of Oxford in 2014, reshaping image classification. With 16 layers, VGG16 has become a standard in this field, delivering state-of-the-art results on benchmark datasets like ImageNet. One of VGG16's key strengths is its flexibility. It can handle different image-arrangement tasks, including object detection, scene grouping, and individual identification (Picault, 2010). Its strong precision has established its standing, reliably achieving top-level performance across various datasets. Proficiency is another sign of VGG16. Despite its depth, it remains generally efficient, making it suitable for ongoing applications where speed is critical.

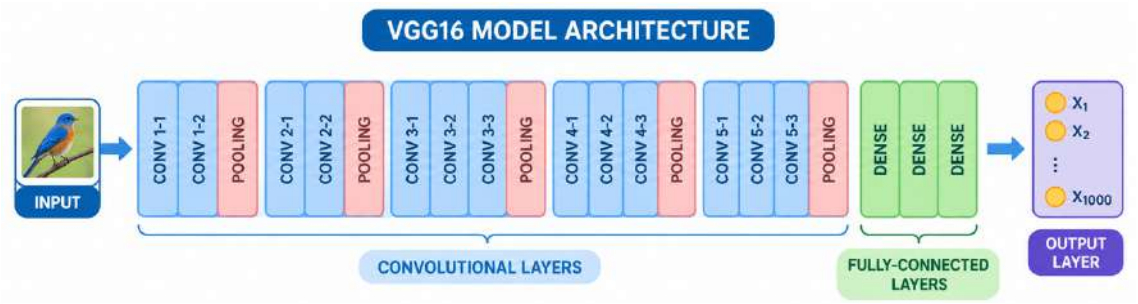


Fig. 4. Model architecture

G. Transfer learning & VGG16

Transfer learning, a key AI technique, involves reusing a model trained on one task as a starting point for another assignme-nt. This strategy is valuable when you have limited information for the next task or when the two tasks are related. VGG16, a convolutional neural syste-m (CNN), stands out as an ideal example of a pre prepared model re-asonable for transfer learning. Initially trained on the ImageNet database, which contains more than 14 million images across 1000 classes, VGG16 performs strongly on various image-related tasks.

Using transfer learning with VGG16 comes with a couple of considerations. Its viability may diminish if the information used differs substantially from what VGG16 was originally trained on. In such case-s, transfer learning may prove inadequate, and building another model from scratch may be more- advantageous. Despite these disadvantages, transfer learning with VGG16 remains a useful asset for developing AI models, particularly in situations with limited data access. It also serves as a strong approach to improving model performance while handling large or imbalanced datasets. Consequently, while it is important to understand its limitations, transfer learning with VGG16 remains a significant methodology in many AI applications.

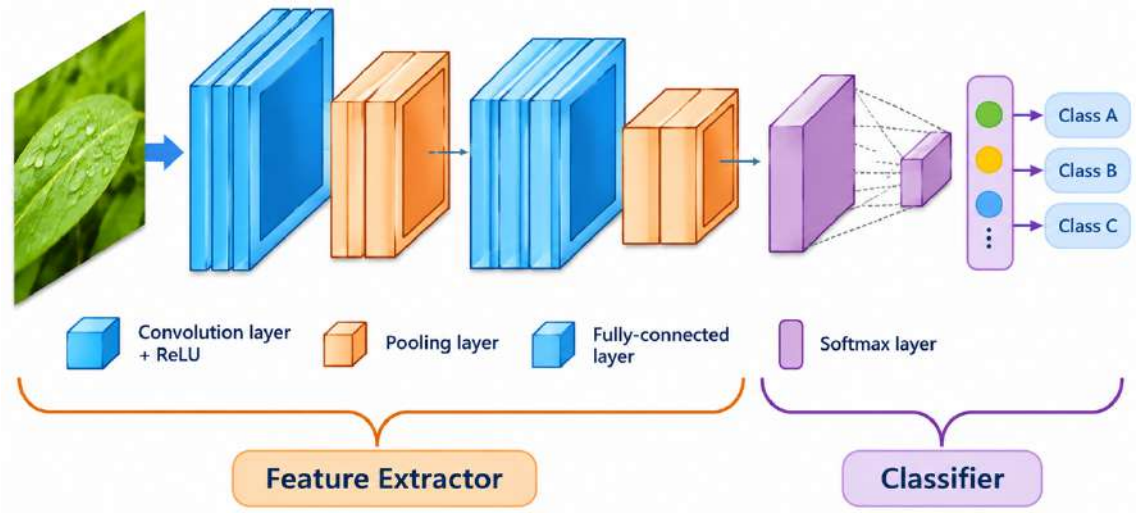


Fig. 5. Transfer Learning Architecture

The model introduced in this study aims to identify deficiencies in sunlight-based chargers, a key part of ensuring their optimal performance. Our model comprises a few layers and tasks designed to handle images and identify different kinds of issues. The model begins with an information layer designed to handle images of different sizes and channel counts, which are common in sunlight-based charger imagery. Next, the data goes through preprocessing steps, such as cropping and data augmentation, to prepare it for further processing.

Our model centers on the VGG16 convolutional neural network (CNN), renowned for its effectiveness in image classification tasks. VGG16 processes the image data, extracting key features indicative of potential shortcomings in solar-powered chargers. After the VGG16 layers, we apply global average pooling, which consolidates the feature maps while retaining their essential information. This step helps improve the data and keeps the model from becoming excessively complex.

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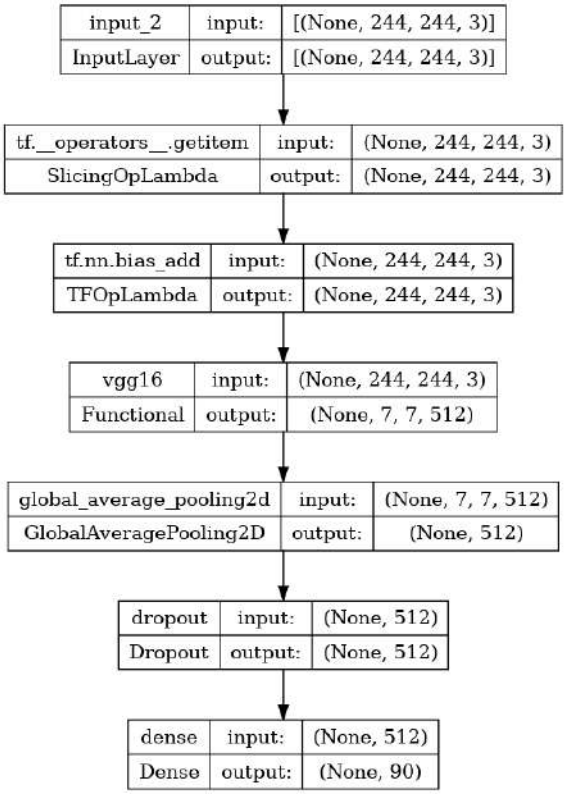


Fig. 6. Architecture Flowchart

To improve the model's power and reduce overfitting, we add a dropout layer that randomly deactivates a few feature units during training. A thick layer serves as the output layer, making an interpretation of the extracted features into predictions regarding the presence of shortcomings in the solar-powered chargers. Our model engineering is customized to really handle sun-powered charger pictures, extract significant elements utilizing VGG16, and make precise expectations for shortcoming recognition. By using advanced deep learning methods, we aim to advance efficient defect-detection frameworks for solar-powered chargers, which is important for maintaining their optimal performance and lifespan.

In our examination of distinguishing deficiencies, we closely considered how well our model learned from the training data. We checked two significant things: accuracy and loss. Precision tells us how often the model was correct when predicting issues in the training data. Higher precision implies the model learned well from the information. Misfortune, then, measures how close the model's predictions were to the real outcomes. A lower misfortune estimate is better because it implies the model's expectations were very close to the actual outcomes. By monitoring these two metrics, we could see how well our model was learning and whether it would perform well at identifying faults in real-world solar chargers.

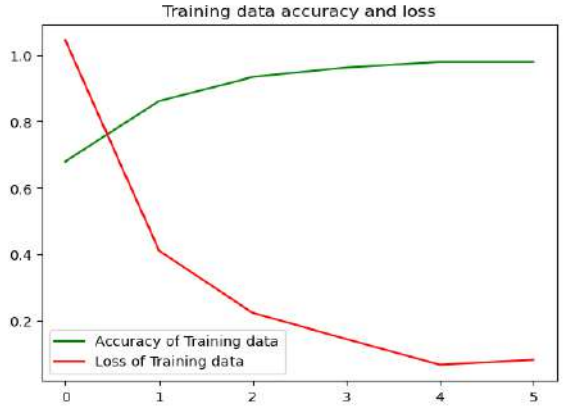


Fig. 7.(a) Training Data Accuracy and Loss

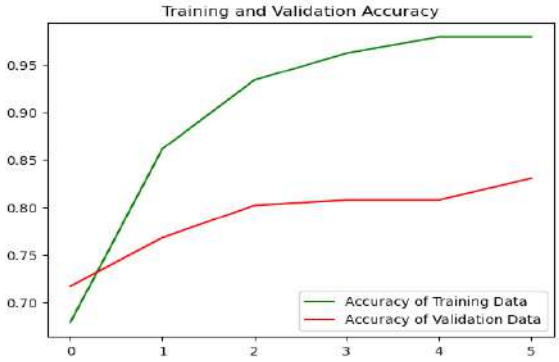


Fig. 8.(b) Training Data Accuracy and Loss

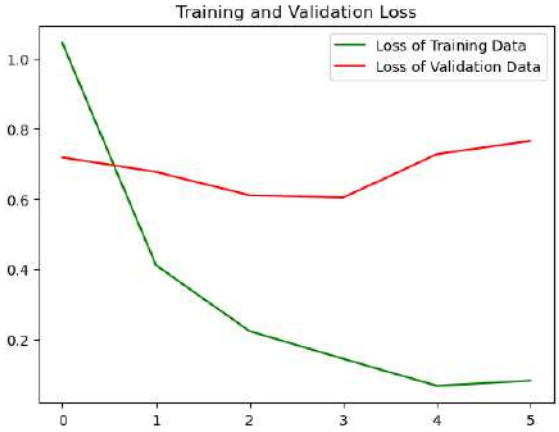


Fig. 9.(c) Training Data Accuracy and Loss

II. Result Classification

In our examination aimed at further developing shortcoming discovery in sun-powered chargers, we conducted extensive trials to assess our model's performance. Through extensive testing and evaluation, we obtained key results that highlight the model's ability to accurately detect different shortcomings in solar chargers. In particular, our model shows a misfortune of 0.7652, indicating the gap between predicted and actual outcomes during training and testing. The model also achieves a noteworthy accuracy of 83.05%, reflecting the proportion of correctly classified cases among all instances assessed.

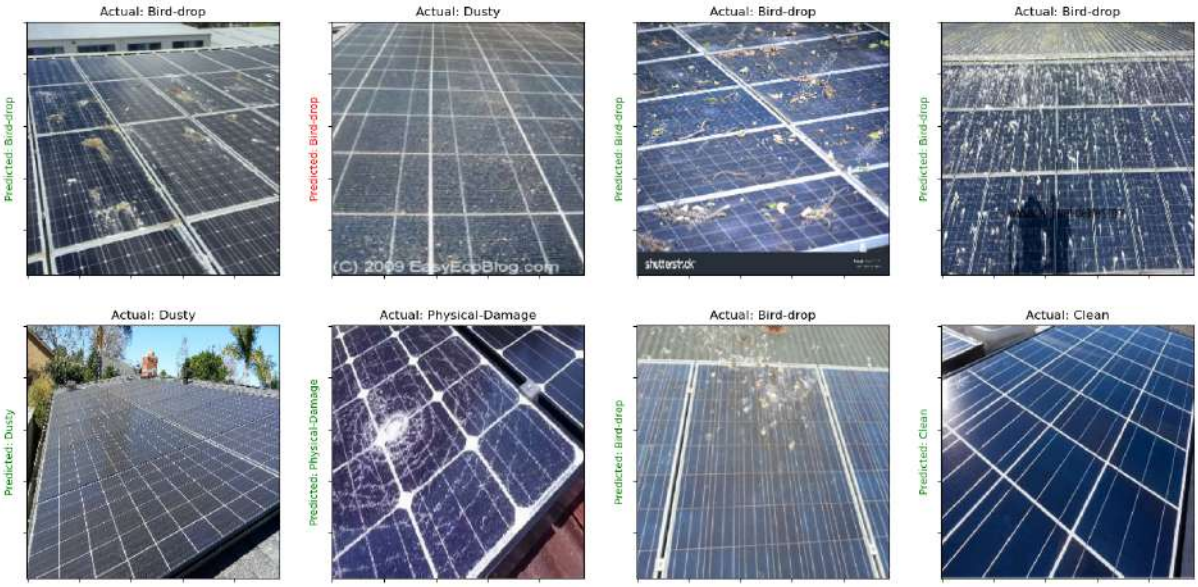




Fig. 10. Fault detection of Type of debris on solar panel

These outcomes have major implications for solar-powered charger maintenance and performance monitoring. By performing strongly in defect detection, our model shows promise in helping solar energy operators identify and resolve issues quickly, reducing downtime and improving energy production efficiency. The high precision rate achieved by our model shows its strong ability to recognize various issues, from dust accumulation to electrical faults, and provides actionable insights to support teams. The strong results from our model's classification highlight its potential as a practical tool for improving the reliability and efficiency of solar energy systems, ultimately supporting the advancement of sustainable energy solutions.

III. Conclusion

All in all, our examination highlights the basic significance of identifying different types of flotsam and jetsam and harm on sunlight-powered chargers to guarantee their ideal performance and energy generation (Rani et al., 2013). We have illustrated the importance of addressing issues like residue buildup, snow accumulation, bird droppings, and physical and electrical damage, all of which can affect solar charger efficiency and reliability. Using various AI classifiers, our review has investigated the feasibility of accurately detecting these surface imperfections. By harnessing the power of human reasoning, we aim to develop a model that can reliably distinguish and classify these irregularities with high accuracy. The results of our examination hold critical importance for the improvement of cutting-edge observing frameworks for sunlight-powered chargers (Sun et al., 2018). By enabling timely intervention and support, our AI-based defect-location approach can improve the productivity, reliability, and lifespan of photovoltaic systems. Eventually, this adds to the more extensive objective of accomplishing a reasonable and versatile sustainable power foundation

Author Contributions

The author declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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This research did not involve human or animal subjects and therefore, did not require ethical approval.

Declaration of Conflicting Interests

The author declared that generative AI was used in the creation of this manuscript. The author sincerely acknowledges the use of AI tools, which contributed to editing and improving the readability of this article. However, the content, ideas, and conclusion presented are entirely the work of the author, reflecting their original research and insights. Any alternative text (alt text) provided alongside figures in this article has been generated by Frontiers with the support of artificial intelligence and reasonable efforts have been made to ensure accuracy, including review by the authors wherever possible. If you identify any issues, please contact us.

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Data Availability

Explain where and how the data supporting the findings of this study can be accessed, including any repository links, digital object identifiers (DOIs), or specific access instructions. Indicate whether the data are openly available, available upon reasonable request, or subject to restrictions (e.g., due to privacy, ethical, or legal considerations). If the data are not publicly available, please provide a clear justification. Additionally, specify the type of data shared (e.g., raw data, processed data, analysis scripts), and ensure that all shared datasets are properly anonymized if they involve human participants.

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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The author(s) declare that no artificial intelligence (AI) or AI-assisted tools were used in the preparation of this manuscript.

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Recognize those who helped in the research, especially funding supporters of your research. Include individuals who assisted you in your study: advisors, financial supporters, or other supporters (e.g., proofreaders, Typists, and suppliers) who may have provided materials. Do not acknowledge one of the authors' names.

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