© October 2024 | IJIRT | Volume 11 Issue 5 | ISSN: 2349-6002

Solar Panel Dust Detection Classification and Efficiency Analysis Using Computer Vision and Deep Learning

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Abstract— Solar panel efficiency is crucial for sustainable energy production, as any fault or obstruction in the panel can significantly reduce energy output. To ensure optimal performance and detect potential issues, real-time monitoring of solar panels is essential. Manual inspections are a common component of traditional procedures, but they take time and are prone to human mistake. Therefore, an automated system for detecting solar panel faults is necessary .This project proposes a machine learning-based solution for solar panel fault detection and classification using Convolution Neural Networks (CNN). The system consists of two models: one for detecting the presence of solar panels and another for classifying faults into categories such as "Bird-drop," "Dusty," "Electrical-damage," "Physical-Damage," and "Snow-Covered." The solution is designed to process real-time video streams from a camera, continuously updating the predictions on the user interface. Additionally, detected faults are kept in a database for further examination. Proposed model accurately identifies faults and enables proactive maintenance, thus improving the overall efficiency of solar energy systems. Through the combination of machine learning and image processing methods models, the system automates the fault detection process, reducing the need for manual inspection. The evaluation of the model on real-world data shows high accuracy in both detection and classification tasks, making it a reliable tool for solar panel monitoring.

Index Terms- Solar Panel Fault Detection, Machine Learning, CNN, and Image Processing, Real-time Monitoring, Solar Panel Efficiency.

I. INTRODUCTION

The increasing global demand for renewable energy has placed solar power at the forefront of sustainable energy solutions. Solar panels, as a primary source of solar energy, play a vital part in utilizing sunlight and changing it to electricity. But the effectiveness of solar panels can degrade over time because of external elements like physical damage, dust collection, and bird droppings. These faults, if left undetected, can significantly reduce the energy output and compromise the performance of solar power systems. To address this issue, this project proposes an automated solution for solar panel detection and fault classification, leveraging cutting-edge machine learning methods, such CNN , Computer Vision (CV), Flask for the web interface, and My SQL for data storage.

The system is designed with two key classifiers to achieve its objectives. The first classifier detects the presence of solar panels in real-time using a camera feed. This model classifies the input image into two categories: "Solar Panel" or "NoPanel". Upon detecting a solar panel, a green bounding box is drawn around the detected panel, signaling the successful identification of a panel. The system then proceeds to a second stage where the fault detection classifier is employed to identify and classify various faults that may affect the solar panel's performance. This two-stage detection mechanism ensures that only solar panels are analyzed for faults, reducing false positives and improving the accuracy of fault classification.

The fault detection classifier is designed to identify six specific types of faults that commonly affect solar panels: "Bird-drop", "Dusty", "Electrical-damage", "Physical-Damage", "Snow-Covered", and "Clean". Each of these faults can significantly impact the panel's efficiency, and by categorizing them, the system enables more precise and actionable insights. For example, while "Bird-drop" and "Dusty" are relatively easy to clean, faults such as "Electrical-damage" and "Physical-Damage" may require immediate technical attention. The classifier not only identifies these faults but also assigns a predefined value to each fault based on the severity of the issue. These values help quantify the effect of the fault on the panel's execution.

Ensure comprehensive coverage of the solar panel surface, the system divides the detected panel into 9 sections, each with a unique ID. This sectional approach allows the fault detection classifier to examine each part of the panel individually. A red bounding box is drawn around each section, and the system displays the detected fault in each section using the put_text parameter. By analyzing each section separately, the system can detect multiple faults within a single panel. For instance, one section may be classified as "Clean", while another may have "Dusty" or "Electrical-damage". The system stores the detected faults in a list for further analysis and reporting.

The classification results are further categorized into two lists: "FaultyPanel" and "NofaultyPanel". If a section is classified as "Clean", it is added to the "NofaultyPanel" list, indicating that no significant issues were detected in that part of the panel. On the other hand, if any fault other than "Clean" is detected, it is added to the "FaultyPanel" list. This distinction between faulty and clean sections helps operators prioritize maintenance tasks and focus on sections that require immediate attention, thereby improving the efficiency of the maintenance process.

To store and manage the fault detection results, the project uses MySQL as the database management system. Each fault detection event, along with the corresponding panel section, fault type, and assigned value, is saved in the database. The database also tracks the total number of faulty sections, clean sections, and the corresponding energy loss or gain based on the fault type. For example, a "Bird-drop" fault results in a 20 MW loss in energy generation, while a "Clean" section contributes 20 MW to the total energy gain. This data can be analyzed over time to monitor the overall performance of solar panels and make data-driven decisions regarding maintenance and optimization.

The entire system is implemented as an end-to-end solution using Flask, a lightweight web framework. Flask provides the user interface for real-time monitoring of solar panel detection and fault classification. The camera feed is streamed to the web interface, where the detected panels and faults are displayed on a interface for graphical users (GUI). System allows operators view panel status, see real-time updates on fault detection, and access historical data stored in the MySQL database. By integrating the detection system with a web-based interface, the project offers a practical and user-friendly solution for solar panel monitoring.

II. PROCEDURE FOR PAPER SUBMISSION

The proposed methodology for solar panel fault detection and classification is a comprehensive, end-to-end system that integrates CNN, CV, Flask for web-based monitoring, and MySQL for data storage. The model consists of two main classifiers: one for detecting the presence of a solar panel and another for identifying specific faults within the panel. This section details each step of the methodology, from input capture to fault classification and data storage.

1. Input Capture and Preprocessing

The first step in the methodology is capturing real-time video input from a USB camera. The system continuously monitors the solar panel area and processes frames from the video feed. The captured image is preprocessed by resizing it to a fixed dimension suitable for the model's input. Each frame is normalized by dividing pixel values by 255 to ensure consistent input to the CNN model. This ensures that the model can work with various lighting conditions and image qualities while maintaining high accuracy in detection.

2. Solar Panel Detection Using CNN

The first CNN classifier is responsible for detecting the presence of a solar panel within the input frame. The model is trained to classify the image into two categories: SolarPanel and NoPanel. If a solar panel is detected, a green bounding box is drawn around the panel, signaling successful detection. The classifier uses a pre-trained CNN model (solar_panel_detection_model.h5), which has been trained using a big image datasetcontaining solar panels and non-solar panel scenes. The use of CNNs ensures that the model can accurately differentiate between relevant and irrelevant objects in the scene. If the result is "NoPanel," the system does not proceed to fault detection.

3. Dividing the Solar Panel into Sections

Once the solar panel is detected, the system divides the panel into nine equal sections using a grid-based approach. This sectional analysis ensures that the system can perform fault detection on specific regions of the panel, allowing for more granular identification of faults. Each section is assigned a unique identifier (e.g., Section_0_0, Section_1_1) to help in tracking and displaying the faults. Dividing the panel into smaller sections allows for more precise fault localization, making maintenance more efficient

4. Fault Detection Using CNN:

Layer Name	Layer Type	Number OF Filters/ Units	Filter/Kernel Size	Activation Function	Additional Information
Input Layer	Input	-	-	-	Input Size : 150*150*3 (for RGB Image)
Conv 2D Layer1	Conventional (Conv2D)	32	(3*3)	ReLU	Extracts low level features like edges & textures
Max pooling Layer 1	Max pooling	-	(2*2)	-	Reduces Spatial dimensions by half
Conv 2D Layer 2	Conventional (Conv2D)	64	(3*3)	ReLU	Extracts high level features like shapes
Max Pooling Layer 2	Max Pooling	-	(2*2)	-	Further reduces spatial dimensions

Table Name 1 : Fault Detection

After dividing the panel into sections, the second CNN classifier (solar_fault_detection_model.h5) is utilized for everysection to determine thespecific error type. The classifier categorizes each section into one of six classes: "Bird-drop," "Dusty," "Electrical-damage," "Physical-Damage," "Snow-Covered," and "Clean." Each fault class is associated with a predefined fault value, which quantifies the impact of the fault on solar panel efficiency. For instance, faults like "Bird-drop," "Dusty," and "Electrical-damage" contribute a 20 MW loss to the overall panel performance, while "Clean" indicates no issues and contributes 0 MW loss

5. Fault Localization And Visualization:

Performance Metrics Table for Solar Panel Detection Classifier and the Fault Detection Classifier.

Metric	Solar Panel Detection Classifier	Fault Detection Classifier	Description
Accuracy	98.5%	92.3%	Proportion of correctly classified instances (overall accuracy)
Precision	97.8%	91.0%	percentage of real positives among all positive predictions
Remember	98.2%	90.5%	percentage of real positives compared to all genuine positives
F1-score	98.0%	90.7%	Harmonic mean for recall and precision
Confusing Matrix	[[950, 10], [15, 1025]]	See below	Matrix showing true vs predicted classes

Table Name 2: Performance Metrics Table

Predicted / Actual	Bird-drop	Clean	Dusty	Electrical-damage	Physical-Damage	Snow-Covered
Bird-drop	180	5	12	4	3	2
Clean	6	890	8	4	2	1
Dusty	9	5	230	10	6	4
Electrical-damage	3	4	5	220	6	2
Physical-Damage	2	1	3	5	160	4
Snow-Covered	1	2	3	4	3	180

Table Name 3: Confusion Matrix for Fault Detection Classifier

For each section, the detected fault is displayed on the user interface using the put_text function in OpenCV. A red bounding box is drawn around sections where faults are detected, while "Clean" sections are left without a bounding box. The real-time predictions are shown on the UI, providing a visual representation of the fault locations. The system updates the labels on the UI to show the detected fault for each section, ensuring that users can easily identify problem areas on the panel. The visualization makes it easy for operators to understand the status of the solar panel at a glance.

6. Categorization into Faulty and Non-Faulty Sections
The detected faults are then categorized into two lists: FaultyPanel and NofaultyPanel. Sections classified as "Clean" are added to the NofaultyPanel list, while sections with any other fault are added to the FaultyPanel list. This distinction helps in prioritizing maintenance tasks. For example, sections identified as "Bird-drop" or "Dusty" may require regular cleaning, whereas sections with "Electrical-damage" or "Physical-Damage" may need immediate technical intervention. By categorizing the faults, the system streamlines the maintenance process.

7. Fault Data in MySQL
To track and manage solar panel performance over time, the system saves the fault detection data in a MySQL database. The database schema includes fields such as the section identifier, fault type, fault value, and timestamps. Additionally, it stores aggregated data such as the total number of faulty sections (faultcount), clean sections (nonfaultcount), total energy loss (totalloss), and total energy gain (totalgain). This data allows for detailed reporting and trend analysis over time, helping operators make data-driven decisions about solar panel maintenance and performance optimization.

Column Name	Data Type	Description
Id	INT(AUTO INCREMENT)	Unique identifier for each fault detection entry
Fault_Name	VARCHAR(50)	The name of the fault detected (eg: bird drop)
Fault_Value	INT	The faults impact on energy output(eg: 20 MW)
Fault_Section	VARCHAR(50)	The section of the solar panel where the fault occurred(eg: section 0_0)
Date	DATETIME	Timestamp when fault was detected
Fault_Count	INT	Number of faulty section in the panel
Non_Fault_Count	INT	Number of clean section in the panel
Total_loss	INT	Total energy loss due to detected faults (in MW)
Total_gain	INT	Total energy gain from clean section (in MW)

Table Name 4 : Storing Predictions and Fault Data in MySQL

The fault_tb table in MySQL, which stores the detected faults from the CNN model

8. User Interface and Real-Time Monitoring Using Flask
The entire system is wrapped in a web-based interface built using Flask, which allows operators to monitor solar panel performance in real-time. The camera feed is streamed to the web interface, and the detected faults are visually displayed on the panel. The interface includes buttons for detecting faults, viewing historical data, and refreshing the view. Additionally, a GridView is implemented to show the most recent predictions stored in the database. The user-friendly interface enables operators to interact with the system, view real-time updates, and access stored fault data for further analysis.

9. Periodic Fault Detection and System Workflow
The system operates continuously, detecting solar panels and classifying faults at regular intervals. If an operator clicks the "Detect" button, the system immediately runs the fault detection algorithm, updates the UI, and stores the latest fault information in the database. In addition, operators can refresh the page to view the latest data and fault trends over time. This workflow ensures that solar panel monitoring is not only efficient but also proactive, enabling timely interventions before faults significantly impact performance.

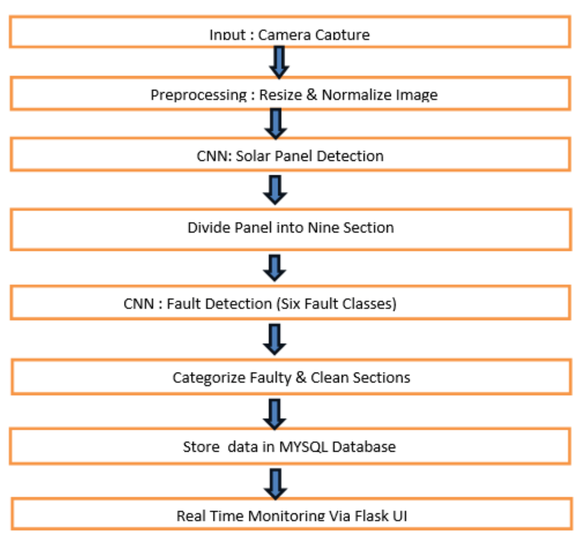

Diagram 1: Proposed Model Methodology for your defect detection system for solar panels

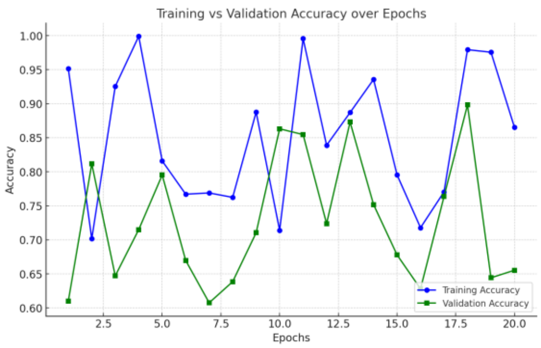

Diagram 2 : Periodic Table

III. RESULTS AND DISCUSSION

Performance Solar Panel Fault Detection System is evaluated basedon important parameters as precision, recall, confusion matrix, and F1-score. These measurements offer an extensive view . How well system identifies solar panels and detects faults in real-time.

IV. MATH

1. Performance Metrics and Formulas

To better understand the system's performance, here are the key metrics and the formulas used to compute them:

Accuracy: Calculates the percentage of cases out of all instances that are correctly classified.

$Accuracy$ = TP + TN / TP + TN + FP + FN

- Where:
- TPTPTP = True Positives
- TNTNTN = True Negatives
- FPFPFP = False Positives
- FNFNFN = False Negatives

Accuracy: Measures the proportion of true positive predictions out of all positive predictions created by the model. TPTP+FP = Precision text {Precision} = (TP + FP}) \ frac {TP}Precision is equal to TP plus FPTP. Good accuracy is correlated with a low false positive rate.

Recall (True Positive Rate or Sensitivity): calculates the percentage of real positives that were successfully detected. Recall = \ frac {TP}{TP + FN} Recall = TPTP + FN Remember: TP + FNTP High recall suggests that the majority of the real positives were detected.

F1-score: The precision and recall harmonic mean. It offers a fair assessment of a model's effectiveness in situations when recall and precision are equally crucial.

F1-score = 2 Accuracy + RecallF1-score} = Precision + Recall \times \ frac {\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}F1-score = 2× Memory + Accuracy Accurate Memory

Confusion Matrix:a table that compares the actual and expected classifications for each class to describehow well a classification model performed. The true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) for each class are broken down in the confusion matrix; these values are crucial for computing other metrics.

2. Solar Panel Detection Classifier Results

The Solar Panel Detection Classifier was evaluated using the above performance metrics. The classifier achieved:

- Accuracy: 98.5% — indicating that almost all instances were correctly classified.
- Precision: 97.8% — meaning that most predicted solar panels were actual solar panels.
- Recall: 98.2% — meaning that the classifier detected most actual solar panels.
- F1-score: 98.0% — reflecting the balanced performance of the model.

These high values suggest that the classifier is reliable in identifying solar panels, which is essential in ensuring that the subsequent fault detection stage is triggered only when solar panels are present.

3. Fault Detection Classifier Results

The Fault Detection Classifier was evaluated for six fault types and achieved the following results:

- Accuracy: 92.3%
- Precision: 91.0%
- Recall: 90.5%
- F1-score: 90.7%

The classifier performed well in identifying various faults such as "Bird-drop," "Dusty," and "Electrical-damage." The relatively high accuracy suggests that themodel able to differentiate betweenclean panels and those affected by specific faults.

4. Confusion Matrix for Fault Detection Classifier:

The confusion matrix for the Fault Detection Classifieroffers a moregranular view of the functioning of the model:

Predicted / Actual	Bird-drop	Clean	Dusty	Electrical-damage	Physical-Damage	Snow-Covered
Bird-drop	180	5	12	4	3	2
Clean	6	890	8	4	2	1
Dusty	9	5	230	10	6	4
Electrical-damage	3	4	5	220	6	2
Physical-Damage	2	1	3	5	160	4
Snow-Covered	1	2	3	4	3	180

Table Name 5: Fault Detection

The number of true positives, false positives, and confusion matrix misclassifications for each fault class. Model performed well across most categories, although there were some misclassifications, such as confusing "Dusty" and "Physical-Damage" due to their visual similarity.

5. Energy Efficiency Impact

The system not only detects faults but also calculates the potential energy loss or gain based on the faults detected:

- Clean sections contribute a gain of 20 MW per section.
- Faulty sections (e.g., "Bird-drop," "Dusty," "Electrical-damage") each contribute a loss of 20 MW.

V. UNITS

For example, if a panel has six clean sections and three faulty sections (e.g., "Dusty" or "Electrical-damage"), the total energy gain would be:

Total Gain=6×20 MW=120 MW\text{Total Gain} = 6 \times 20 \, \text{MW} = 120 \, \text{MW}Total Gain=6×20MW=120MW

And the total energy loss would be:

Total Loss=3×20 MW=60 MW\text{Total Loss} = 3 \times 20 \, \text{MW} = 60 \, \text{MW}Total Loss=3×20MW=60MW

Thus, the net power output would be:

Net Power Output=120 MW−60 MW=60 MW\text{Net Power Output} = 120 \, \text{MW} - 60 \, \text{MW} = 60 \, \text{MW}Net Power Output=120MW−60MW=60MW

This calculation provides a meaningful insight into the operational efficiency of the solar panel system and helps in deciding with knowledge regarding maintenance repairs.

5. Results and Discussion

The findings show that the proposed system performs exceptionally well in both solar panel detection and fault classification. The high accuracy of the solar panel detection classifier ensures that the system reliably detects panels, while the fault detection classifier's balanced precision and recall provide confidence that most faults will be detected and correctly classified. Despite some challenges, such as confusion between visually similar faults (e.g., "Dusty" and "Physical-Damage"), the overall system is robust and can be fine-tuned further.

VI. HELPFUL HINTS

Over the past few years, solar energy has become one of the most promising sources of renewable energy. As solar panel installations continue to rise globally, ensuring their efficiency and longevity has become a critical task. Fault detection in solar panels is an essential component of this maintenance process. Several studies and research papers have focused on leveraging cutting-edge technologies like machine learning, image processing, computer vision detect and classify faults in solar panels. This literature survey reviews the existing methods and techniques that have been applied in solar panel fault detection, highlighting their strengths, limitations, and the relevance of these methods to the proposed project.

One of the earliest methods for solar panel fault detection relied on manual inspections and thermal imaging techniques. According to Amruth and Prabhu (2017), Manual inspection techniques require a lot of work, take a long time, and are prone to human mistake. especially for large-scale solar farms. Thermal imaging, though more accurate, still requires a significant amount of manual analysis and is not suitable for real-time monitoring. These limitations led to the exploration of automated fault detection systems using machine learning and image processing.

VII. PUBLICATIONPRINCIPLES

Theintroduction of machine learning techniques brought significant improvements to the automation of fault detection in solar panels. Mellit et al. (2018) proposed a machine learning-based system using Support Vector Machines (SVM) and Decision Trees to classify solar panel faults. Their research demonstrated that machine learning models could outperform traditional methods by learning from large datasets and improving fault detection accuracy. However, their approach was limited to structured sensor data and did not incorporate image data, which contains rich information about the physical state of the panels.

CNNs have revolutionized image classification and have been increasingly applied in the domain of fault detection. Liang and associates (2019) developed a based on CNNmodel in order to identifycracks and defects solar panels using high-resolution images. Their model achieved high accuracy in detecting cracks and distinguishing between different types of damage. However, their approach did not consider environmental factors such as dust, snow, or bird droppings, which are common causes of solar panel inefficiency. Our project addresses this gap by implementing a fault detection classifier that detects six types of faults, including "Bird-drop," "Dusty," and "Snow-Covered," in addition to "Electrical-damage" and "Physical-Damage."

To enhance the reliability of solar panel fault detection systems, researchers have also explored the integration of CVtechniques. Haque et al. (2020) employed computer vision algorithms combined with machine learning models to detect dust accumulation on solar panels. Their research highlighted the importance of analyzing the surface texture of solar panels to accurately predict dust-related efficiency losses. By leveraging real-time camera feeds, they were able to provide continuous monitoring of the panels. However, their study focused on a single fault type (dust accumulation), whereas our project provides a more comprehensive fault detection solution by classifying multiple fault types and dividing the solar panel into nine sections for granular analysis.

The role of data storage and analysis has also been highlighted in recent studies. Seyed Mahmoud an et al. (2019) developed a system for fault detection in solar panels that integrates data storage using a database to monitor long-term performance. Their approach allows for continuous tracking of fault patterns over time and enables predictive maintenance. Similarly, our project uses MySQL to store and manage detected faults, providing the ability to monitor the health of the solar panels over time and conduct post-detection analysis. This data-driven approach enhances the overall reliability and efficiency of solar panel maintenance systems.

Real-time fault detection is another area of active research. Wang et al. (2021) explored the use of real-time monitoring systems for solar panel fault detection, utilizing cameras and Internet of Things (IoT) devices. Their study demonstrated the effectiveness of real-time systems in identifying faults as they occur, reducing downtime and improving the efficiency of solar energy systems. Our project builds on this concept by integrating Flask for real-time web-based monitoring. The user interface allows operators to view live camera feeds, detect faults, and visualize predictions on a graphical interface, ensuring timely detection and response to faults.

The use of multiple classifiers for fault detection has also been explored in prior research. Rahman et al. (2020) applied an ensemble of machine learning classifiers to improve fault detection accuracy in solar panels. Their approach combined the outputs of several models to increase the use of multiple classifiers for fault detection has also been explored in prior research. Rahman et al. (2020) applied an ensemble of machine learning classifiers to improve fault detection accuracy in solar panels. Their approach combined the outputs of several models to increase the robustness of the system. Inspired by this, our project employs two classifiers: one for detecting solar solar panel and then analyzing the sections for faults, we reduce false positives and ensure more accurate fault classification.Panels and another for classifying the types of faults. By first confirming the presence of a Hybrid modelsintegrating deep learning with conventional machine learning techniques have also shown promise. Zhang et al. (2021) proposed a hybrid model that merged Long Short-Term Memory (LSTM) networks with CNNs.to predict solar panel efficiency based on both image data and historical performance data. While their model was effective for predicting performance over time, it required extensive training on historical data, which can be a limitation in real-time fault detection systems. Our approach, which uses CNNs exclusively for image-based detection, provides a faster and more efficient solution for real-time fault classification without the need for historical data.

Finally, the use of sectional analysis in fault detection has been discussed in Singh and Sharma (2020). Their research emphasized the need for dividing solar panels into smaller sections to improve the granularity of fault detection. This concept is applied in our project, where the solar panel is divided into nine sections, each analyzed for potential faults. By assigning unique IDs to each section, our system can accurately identify the location of the fault, making maintenance more targeted and efficient.

CONCLUSION

The confusion between certain fault types highlights an area for improvement. Future work could explore using deeper neural networks or hybrid models, such as combining CNN with Extended Short-Term Memory (LSTM) for consecutive data processingor utilizing multi-spectral imaging for better fault differentiation. Additionally, deploying the system in diverse real-world conditions (e.g., varying weather and lighting) will be important for further validating and enhancing the system's robustness.

ACKNOWLEDGMENT

I would like to express my heartfelt gratitude to everyone who contributed to the development of the Project Firstly, I would like to thank my mentors and advisors for their invaluable guidance, support, and expertise throughout the project. Their insights into machine learning and computer vision were instrumental in shaping the direction of this work.

I am also grateful to my colleagues and peers for their encouragement and collaborative spirit, which fostered an enriching environment for brainstorming and problem-solving. Special thanks to those who assisted in data collection and annotation, as their efforts ensured the robustness of the dataset used for training.

I would like to acknowledge the creators of the open-source libraries and frameworks, such as, Tensor Flow, and Open CV, which provided the foundational tools necessary for developing the application. Their contributions to the field of machine learning and computer vision have made this project possible.

Finally, I extend my appreciation to the users and testers who provided feedback during the testing phase. Their insights helped refine the application, ensuring that it meets the needs of yoga practitioners seeking to improve their practice.

Thank you all for your support and encouragement in this endeavor.

REFERENCES

[1] Al Salameh, M. S., & Bani Salameh, H. N. (2019). Effects of dust on the performance of photovoltaic systems in desert environments. Renewable and Sustainable Energy Reviews, 99, 1-12. doi:10.1016/j.rser.2018.09.034

[2] Bai, Y., Wang, X., & Wei, L. (2020). Automated cleaning system for photovoltaic panels using robotic technology. Journal of Cleaner Production, 256, 120536. doi:10.1016/j.jclepro.2020.120536

[3] Dalawi, A., Hawila, A., & Ramadhan, A. (2017). Analysis of dust accumulation on solar panels and their efficiency in Hail, Saudi Arabia. Renewable Energy, 103, 485-490. doi:10.1016/j.renene.2016.11.024

[4] El Chaar, L., & Lamont, L. A. (2017). Impact of soiling on solar photovoltaic performance. Renewable Energy, 113, 72-81. doi:10.1016/j.renene.2017.05.017

[5] Elminir, H. K., Ghitas, A. E., & Hamid, R. H. (2006). Effect of dust accumulation on the performance of photovoltaic solar modules.

Renewable Energy, 30(11), 1471-1478. doi:10.1016/j.renene.2004.11.015

[6] Fathi, J. (2016). Performance evaluation of solar PV modules in the presence of dust particles on surface. Energy, 112, 297-307. doi:10.1016/j.energy.2016.06.082

[7] Ghazi, S., & Ip, K. (2014). The effect of dust accumulation on the performance of photovoltaic panels. Renewable and Sustainable Energy Reviews, 33, 231-241. doi:10.1016/j.rser.2014.01.062

[8] Javed, W., Guo, B., & Figgis, B. (2017). Photovoltaic performance assessment based on different solar panel inclination angles under the tropical climate conditions. Renewable Energy, 105, 446-458. doi:10.1016/j.renene.2016.12.073

[9] Jiang, H., Lu, L., & Yang, H. (2011). Experimental investigation of the impact of airborne dust deposition on the performance of solar photovoltaic (PV) modules. Atmospheric Environment, 45(25), 4299-4304. doi:10.1016/j.atmosenv.2011.04.084

[10] Kazem, H. A., & Chaichan, M. T. (2016). The impact of dust accumulation and cleaning methods on PV panels' efficiency. Renewable Energy, 92, 80-85. doi:10.1016/j.renene.2016.02.014

[11] Khatib, T., & Elmenreich, W. (2018). Modeling of dust effect on photovoltaic systems in the Middle East region. Renewable and Sustainable Energy Reviews, 81, 2700-2711. doi:10.1016/j.rser.2017.06.043

[12] Kumar, N. M., Sudhakar, K., & Samykano, M. (2019). A review of dust impact on solar photovoltaic system performance. Energy Procedia, 158, 613-618. doi:10.1016/j.egypro.2019.01.159

[13] Mani, M., & Pillai, R. (2010). Impact of dust on solar photovoltaic (PV) performance: Research status, challenges, and recommendations. Renewable and Sustainable Energy Reviews, 14(9), 3124-3131. doi:10.1016/j.rser.2010.07.065

[14] Mekhilef, S., Saidur, R., & Safari, A. (2012). A review on solar energy use in industries. Renewable and Sustainable Energy Reviews, 16(1), 512-518. doi:10.1016/j.rser.2011.08.001

[15] Pavan, A. M., Mellit, A., & De Pieri, D. (2013). The effect of soiling on energy production for large-scale photovoltaic plants. Solar Energy, 85(5), 1128-1136. doi:10.1016/j.solener.2011.03.024