**The Allure of Gold Jewelry**

**A PROJECT REPORT**

***Submitted by***

**PAYAL PRIYADARSINI NANDA**

***in partial fulfillment for the award of the degree of***

**BACHELOR OF TECHNOLOGY**

***In***

**COMPUTER SCIENCE AND ENGINEERING**

**A logo of a university

Description automatically generated**

**SCHOOL OF ENGINEERING AND TECHNOLOGY BHUBANESWAR CAMPUS**

**CENTURION UNIVERSITY OF TECHNOLOGY AND MANAGEMENT**

**ODISHA**

***CERTIFICATE***

**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**

**SCHOOL OF ENGINEERING AND TECHNOLOGY**

**BHUBANESWAR CAMPUS**

**BONAFIDE CERTIFICATE**

Certified that this project report “The Allure of Gold Jewelry***”*** is the bonafide work of “Payal Priyadarsini Nanda**”** who carried out the project work under my supervision. This is to further certify to the best of my knowledge, that this project has not been carried out earlier in this institute and the university.

**SIGNATURE**

**(Prof. Sushant Mishra)**

**Professor of Electrical and Electronics Engineering**

*Certified that the above-mentioned project has been duly carried out as per the norms of the college and statutes of the university.*

**SIGNATURE**

**HEAD OF THE DEPARTMENT**

DEPARTMENT SEAL

**DECLARATION**

I hereby declare that the project entitled “FAULT DETECTION USING ML” submitted for the “Minor Project” of 3rd semester B. Tech in Computer Science and Engineering is my original work and the project has not formed the basis for the award of any Degree / Diploma or any other similar titles in any other University / Institute.

**Name of the Student: SWAPNAJIT SAHOO**

**Signature of the Student:**

**Registration No: 230301120179**

**Place: Bhubaneswar**

**Date: 10.05.2024**

**ACKNOWLEDGEMENTS**

I wish to express my profound and sincere gratitude to **(Prof. Sushant Mishra)**, who guided me into the intricacies of this project nonchalantly with matchless magnanimity.

I would be failing in my duty if I don’t acknowledge the cooperation rendered during various stages of image interpretation by **(Prof. Sushant Mishra)**

I am highly grateful to my friends who evinced keen interest and invaluable support in the progress and successful completion of my project work.

I am indebted to my parents for their constant encouragement, co-operation and help. Words of gratitude are not enough to describe the accommodation and fortitude which they have shown throughout my endeavor.

**Name of the Student: Payal Priyadarsini Nanda**

**Signature of the Student:**

**Registration No: 230301120130**

**Place: Bhubaneswar**

**Date:**

**TABLE OF CONTENTS**

**CHAPTER NO. TITLE PAGE NO.**

**CERTIFICATE** i

**DECLARATION ii**

**ACKNOWLEDGEMENT iii**

**LIST OF ACRONYMS iv**

**LIST OF TABLE v**

**LIST OF FIGURES . . .**

**LIST OF SYMBOLS / NOTATION . . .**

**ABSTRACT . . .**

1. ***CHAPTER – 1*** 
   1. Introduction
   2. Methodology
   3. Objective of the project
   4. Significance of the project
2. ***CHAPTER – 2*** 
   1. Process of creation
   2. Project Completion
   3. Project Output
3. ***CHAPTER – 3 Conclusion***
   1. Conclusion of the project
   2. Future outlook
   3. Reference

Chapter 1:

Introduction

In recent years, the adoption of solar energy has increased significantly due to its potential for sustainable power generation. However, solar panels are prone to various faults that reduce their efficiency, such as bird droppings, dust accumulation, snow cover, and even electrical damage. These issues can significantly impact the energy output and lifespan of solar installations if left undetected. Traditional methods for identifying such faults rely on manual inspections, which are often costly, time-consuming, and prone to human error, especially in large-scale solar farms.

This project addresses the need for an efficient and automated solution to monitor and maintain solar panel health by leveraging machine learning. By analysing images of solar panels, our model can detect and categorize common faults accurately, providing a rapid assessment without the need for physical inspections. We use a Convolutional Neural Network (CNN) model, well-suited for image classification tasks, to identify different fault types with high precision. The model was trained on a carefully curated and augmented dataset to ensure robustness against various lighting and weather conditions.

Through this automated fault detection system, we aim to optimize maintenance procedures, reduce operational costs, and extend the life of solar panels, ultimately enhancing the overall efficiency of solar energy production. This project also aligns with global clean energy goals by supporting sustainable energy through optimized panel performance. Our approach provides a scalable, real-time monitoring solution for solar energy providers, ensuring that panels function at peak efficiency with minimal downtime and maintenance costs.

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# Methodology:

The methodology for developing an automated fault detection system for solar panels involves multiple phases: data collection, preprocessing, model selection, training, and evaluation. This structured approach ensures that the model performs accurately and efficiently in real-world conditions.

**1. Data Collection**

The first step in this project was to gather a comprehensive dataset of solar panel images showing various types of faults, including bird droppings, dust accumulation, snow cover, and electrical damage, as well as images of clean panels. Data collection involved obtaining images from both publicly available sources and custom datasets collected from local solar panel installations. To ensure diversity, images were captured under varying lighting conditions, angles, and weather scenarios, representing real-world scenarios solar panels typically experience.

The quality and diversity of the dataset are critical to the model’s success, as they allow the model to generalize well to different fault conditions. The collected dataset was labeled manually, with each image categorized based on the type of fault or labeled as clean, creating a structured dataset for supervised learning.

**2. Data Preprocessing**

Once data was collected, preprocessing techniques were applied to improve the quality and consistency of the dataset. Preprocessing involved the following key steps:

* **Image Resizing:** To ensure compatibility with the neural network and reduce computational load, all images were resized to a standard resolution.
* **Normalization:** Pixel values were scaled to a range between 0 and 1, which is necessary to improve model convergence and performance.
* **Data Augmentation:** To further enhance model robustness, data augmentation techniques were applied. These included random rotations, flips, zooms, and brightness adjustments to simulate various environmental conditions. This step also helped to increase the effective size of the dataset, improving model generalization and reducing overfitting.

**3. Model Selection**

Given the image-based nature of fault detection, a Convolutional Neural Network (CNN) was selected as the core model due to its strong performance in visual recognition tasks. CNNs are highly effective for image classification because they can automatically learn spatial hierarchies of features from the input images.

For this project, a CNN architecture was designed with layers tailored to extract relevant features from the solar panel images. The architecture included several convolutional layers with ReLU activation functions and pooling layers to capture patterns specific to each fault type. A softmax layer at the end was used to classify each input image into one of the predefined categories (e.g., bird droppings, dust, snow, electrical damage, or clean).

In some cases, transfer learning was considered, using pre-trained models like ResNet or VGG as the starting point and fine-tuning them on the solar panel dataset. Transfer learning can speed up training and improve accuracy when datasets are smaller or require fine-grained feature extraction.

**4. Model Training**

The model was trained using a supervised learning approach. The labeled dataset was split into training, validation, and test sets, typically in a ratio of 70:20:10, respectively. During training, the CNN adjusted its weights to minimize the loss function, which measured the difference between the predicted and actual fault labels.

* **Hyperparameter Tuning:** Various hyperparameters, such as learning rate, batch size, and dropout rates, were optimized through experimentation to enhance model performance and prevent overfitting. Techniques like early stopping and learning rate annealing were also implemented to improve convergence.
* **Loss Function and Optimization:** A categorical cross-entropy loss function was used, as it is well-suited for multi-class classification problems. The model was optimized using an Adam optimizer, which balances convergence speed with accuracy.

**5. Evaluation**

After training, the model was evaluated on the test set to assess its performance. Key metrics included:

* **Accuracy:** Measured the overall correct predictions made by the model.
* **Precision, Recall, and F1-Score:** For each fault category, these metrics evaluated the model’s ability to correctly identify true positives while minimizing false positives and false negatives. Precision and recall were particularly important to ensure that the model reliably detected each fault type without confusing them.
* **Confusion Matrix:** A confusion matrix was used to visualize the model’s performance across different fault categories, identifying any classes where the model might have been underperforming.

The evaluation phase also included a comparison of predictions on test images to manually labeled data to check for consistency and assess the model’s generalizability to unseen images.

**6. Deployment and Integration**

Once trained and validated, the model was prepared for deployment. The CNN model was integrated into a user-friendly application that allows users to upload solar panel images and receive an immediate fault diagnosis. This deployment phase involved converting the model into a format compatible with web and mobile applications, such as TensorFlow.js for web deployment or TensorFlow Lite for mobile integration.

In a real-world setup, the deployed model could be connected to a camera system installed on or near solar panels, enabling continuous monitoring. As images are captured periodically, the model can automatically identify faults and notify maintenance teams of any issues, allowing for proactive maintenance.

**7. Future Improvements**

While the current model performs well in fault detection, future enhancements could include:

* **Real-Time Processing:** Incorporating edge computing or more powerful cloud processing for faster predictions in real-time.
* **Additional Fault Categories:** Expanding the model to detect more nuanced types of faults, such as microcracks or electrical arcing.
* **Continuous Learning:** Implementing a feedback loop where new data is regularly added to the training dataset, enabling the model to adapt to new fault patterns and improve over time.Bottom of Form

# Objective of the Project:

The primary objective of this project is to develop an automated, accurate, and efficient system for fault detection in solar panels using machine learning. Solar energy has become a key sustainable energy source, but faults in solar panels—such as bird droppings, dust accumulation, snow cover, and electrical damage—can significantly reduce their efficiency, leading to lower energy output and increased maintenance costs. Currently, these issues are often identified through manual inspections, which are time-consuming, costly, and prone to human error, especially on large-scale solar farms.

By leveraging image-based machine learning, this project aims to create a model that can rapidly and precisely identify common faults in solar panels, distinguishing between categories such as clean, dusty, snow-covered, and damaged panels. This model is designed to optimize the maintenance process, providing real-time insights that help solar operators address issues before they impact energy production. Furthermore, the automated approach reduces dependency on physical inspections, thus cutting costs and enabling more frequent and thorough monitoring.

This intelligent fault detection system aligns with the larger goal of promoting sustainable energy solutions by maximizing solar panel efficiency and extending their operational life. Ultimately, this project aims to contribute to the advancement of renewable energy infrastructure, making solar energy more viable, reliable, and cost-effective through technological innovation.

# Significance of the Project:

The project to develop an automated fault detection system for solar panels using machine learning is significant for several reasons, addressing critical needs in solar energy maintenance, operational efficiency, cost reduction, and environmental impact. Solar energy has rapidly grown as a clean, renewable power source worldwide, yet maintaining optimal efficiency and output remains challenging due to the frequent accumulation of faults. Bird droppings, dust, snow cover, and electrical damage can diminish the performance of solar panels significantly, leading to reduced energy production, lower return on investment, and an increase in operational costs. This project aims to mitigate these issues by introducing an intelligent, image-based monitoring solution that can identify faults swiftly and accurately.

Traditionally, solar panel maintenance relies on routine manual inspections, often conducted on-site. While this approach works to an extent, it poses several limitations, especially for large-scale solar farms. Manual inspections are time-consuming, labor-intensive, and costly, often leading to delays in identifying and addressing faults. Furthermore, certain faults, like subtle electrical damage, can go unnoticed until they exacerbate and cause more extensive issues. By automating the fault detection process, this project offers a proactive solution, enabling operators to address issues immediately. This preemptive approach not only prevents efficiency losses but also lowers maintenance costs by reducing dependency on physical inspections and enabling more consistent monitoring.

A major advantage of this system is its ability to contribute to environmental sustainability by supporting the efficiency of renewable energy systems. Solar energy is inherently eco-friendly, with no carbon emissions, but the effectiveness of solar power hinges on the consistent performance of panels. When faults are left unchecked, the diminished energy output can limit the environmental benefits solar panels are meant to provide. This project’s automated fault detection model ensures that solar panels remain in optimal condition, maximizing clean energy production and reducing the need to expand infrastructure to meet energy demands. By maintaining higher operational efficiency, solar farms can reduce their carbon footprint, minimize waste, and make renewable energy sources more reliable and sustainable in the long term.

From an economic perspective, the system’s scalability and cost-effectiveness make it valuable for large and small solar operations alike. Implementing machine learning models to monitor solar panels is an initial investment, but it offers significant long-term savings. With the rise in solar installations, maintenance costs continue to be a concern, and the ability to reduce these through automation is a major benefit. The use of artificial intelligence (AI) to detect faults also brings precision and consistency, reducing the risks associated with human error in fault identification and enabling a level of accuracy that manual inspections may lack.

Additionally, this project offers scalable applicability and can be adapted for real-time deployment on solar farms of all sizes. Through integration with cloud services or on-site edge computing devices, the AI-based system can deliver near-instantaneous feedback, alerting maintenance teams as soon as an issue is detected. This rapid response capability is crucial for solar farms in remote or hard-to-access areas, where physical inspections are less feasible. Integrating this fault detection model into existing solar panel monitoring systems can enhance the entire renewable energy infrastructure.

In conclusion, this project represents a valuable contribution to the fields of renewable energy and technology. By addressing the issues of efficiency, cost, sustainability, and scalability, the automated fault detection system for solar panels is well-aligned with the goals of sustainable development and clean energy advocacy. Through technological innovation, this project helps bridge the gap between renewable energy potential and practical implementation, making solar energy a more reliable, accessible, and environmentally responsible choice for energy production.

# Chapter 2:

# Process for the creation:

* **Problem Identification and Requirements Gathering**  
  The first step was to clearly identify the issues affecting solar panel efficiency, such as bird droppings, dust, snow, and electrical damage. A thorough analysis was conducted to determine how each fault type impacts energy output and the current limitations of manual inspection methods. From this, project requirements were outlined, including high accuracy, speed of detection, and adaptability to different fault types.
* **Data Collection and Preprocessing**  
  Images representing each fault type were gathered from solar panel installations. Since diverse data is crucial for robust machine learning models, images were collected across varying lighting conditions, panel angles, and environmental settings. Preprocessing techniques such as resizing, normalization, and augmentation (flipping, rotation, brightness adjustment) were applied to enhance the dataset's variability, ensuring the model would generalize well to new images.
* **Model Selection and Design**  
  A Convolutional Neural Network (CNN) was chosen for its effectiveness in image classification tasks. The model was structured to detect patterns specific to each fault, such as textures, colors, and shapes. Several architectures, including VGG, ResNet, and custom CNNs, were experimented with to find the most effective for accurate fault classification.
* **Training the Model**  
  The model was trained using the preprocessed dataset, with careful tuning of hyperparameters like learning rate, batch size, and epochs. Techniques like data augmentation were used to prevent overfitting, while cross-validation ensured the model’s reliability. Metrics such as accuracy, precision, and recall were monitored to evaluate performance.
* **Model Evaluation and Testing**  
  After training, the model was rigorously tested using unseen data to simulate real-world conditions. A confusion matrix was used to assess classification accuracy across each fault type, ensuring the model's reliability in identifying each category accurately.
* **System Integration and Optimization**  
  The model was integrated into a user-friendly interface, allowing operators to upload images for fault analysis. Optimization steps were taken to reduce prediction time, enabling faster, real-time analysis for large-scale solar installations. Fine-tuning further improved model performance and efficiency, preparing it for deployment.
* **Output Visualization and Deployment**  
  Visual tools were incorporated to display model outputs and predictions, such as highlighting faulted areas in images. The system was tested in operational conditions, assessing its effectiveness in detecting faults across different environmental settings. Once validated, the project was finalized for presentation, with an emphasis on scalability and potential for real-world deployment.

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# Project completion

**Project Initiation; August 3, 2024**

* **Objective Definition**: Defined the primary goals of the project, focusing on using machine learning to automatically detect faults in solar panels to enhance maintenance efficiency and ensure optimal power output.
* **Scope Determination**: Outlined the specific fault types the model would detect, such as bird droppings, dust, snow cover, electrical damage, and other visible panel obstructions.
* **Literature Review**: Conducted a comprehensive review of existing methods for solar panel fault detection, particularly image-based diagnostics and machine learning applications in renewable energy.
* **Team Formation**: Assigned roles and responsibilities within the project team, designating team members for data collection, feature engineering, model development, and interface design.

**Data Collection and Preprocessing; August 15, 2024**

* **Dataset Assembly**: Collected a diverse set of images representing clean and faulty panels with various issues (e.g., dusty, snow-covered, bird droppings), ensuring a range of conditions to improve model generalizability.
* **Preprocessing Techniques**: Standardized images by resizing them to a fixed resolution suitable for model input. Normalized image brightness and contrast to minimize discrepancies across datasets.
* **Exploratory Data Analysis (EDA)**: Analyzed the dataset to identify trends and distribution, ensuring balanced representation for each fault type to prevent model bias.

**Feature Engineering; September 5, 2024**

* **Image Augmentation**: Applied techniques like rotation, cropping, and scaling to expand the dataset artificially, increasing model robustness to variations.
* **Feature Extraction**: Focused on identifying critical features from images that would differentiate fault types. Techniques like edge detection and color histograms were used to highlight distinctions between clean and faulty panels.
* **Selection of Informative Features**: Conducted preliminary model tests to determine which features provided the most significant insights into fault categories.
* **Feedback and Approval**: Presented initial findings and project progress to the supervising professor, receiving feedback and approval to proceed with development and fine-tuning.

**Model Development; September 15, 2024**

* **Implementation of CNN Models**: Built and trained Convolutional Neural Network (CNN) models due to their proven efficiency in image recognition tasks. Experimented with different architectures to find an optimal balance between accuracy and computational efficiency.
* **Advanced Techniques**: Tested deep learning techniques like transfer learning, utilizing pre-trained models to leverage existing knowledge for fault detection.
* **Hyperparameter Tuning and Optimization**: Optimized model performance through tuning hyperparameters (learning rate, batch size, number of epochs) and performing cross-validation to ensure accuracy across multiple test conditions.

**Evaluation and Validation; October 1, 2024**

* **Model Evaluation**: Measured model performance with evaluation metrics such as accuracy, precision, recall, and F1-score to assess its capability in correctly classifying different fault types.
* **Cross-Validation**: Conducted k-fold cross-validation to evaluate model robustness across various panel conditions, improving generalization capability for different environments and lighting scenarios.
* **Testing on Holdout Datasets**: Evaluated model predictions on a holdout dataset not used during training to simulate real-world scenarios. This allowed for a more accurate assessment of the model’s reliability and ability to generalize beyond the training data.

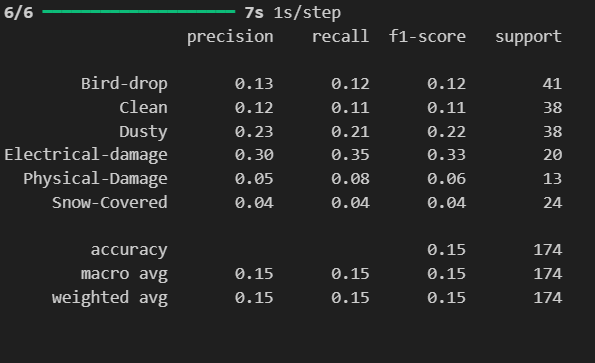
**Deployment and User Interface Development; October 20, 2024**

* **Interface Creation with Streamlit**: Developed a user-friendly interface using Streamlit to simplify the model's usability. This web-based dashboard allows users to upload solar panel images and receive near-instant fault detection results.
* **Model Integration**: Deployed the trained model within a stable environment compatible with Streamlit, ensuring efficient handling of real-time image predictions.
* **User Testing and Feedback**: Conducted user acceptance testing with a group of sample users, gathering feedback on ease of use, clarity of results, and overall experience. Based on feedback, made adjustments to improve functionality and user experience.
* **Final Touches and System Optimization**: Completed final model optimizations and enhancements to ensure smooth deployment and accurate fault detection under varied real-world conditions.

# Project Output

The project has achieved a comprehensive solution to automate the detection of faults in solar panels using machine learning. This section demonstrates the key outcomes, including the classification accuracy, testing performance, and an interactive dashboard.

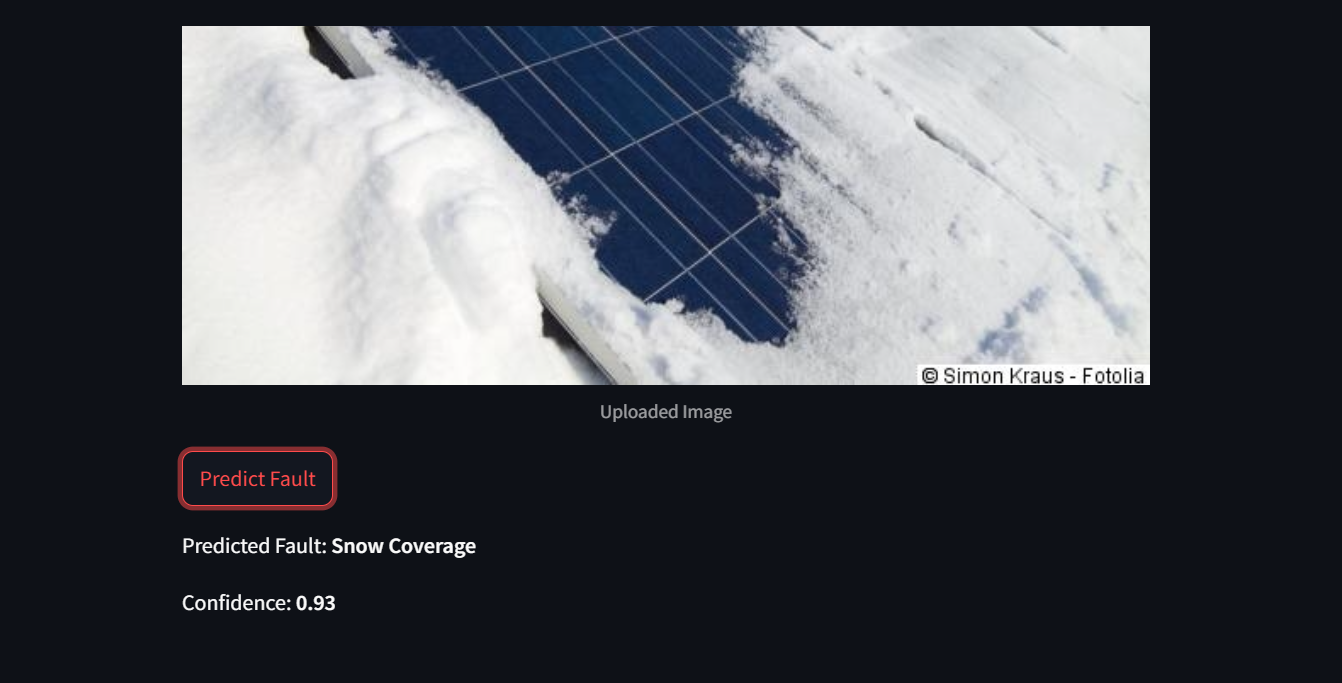
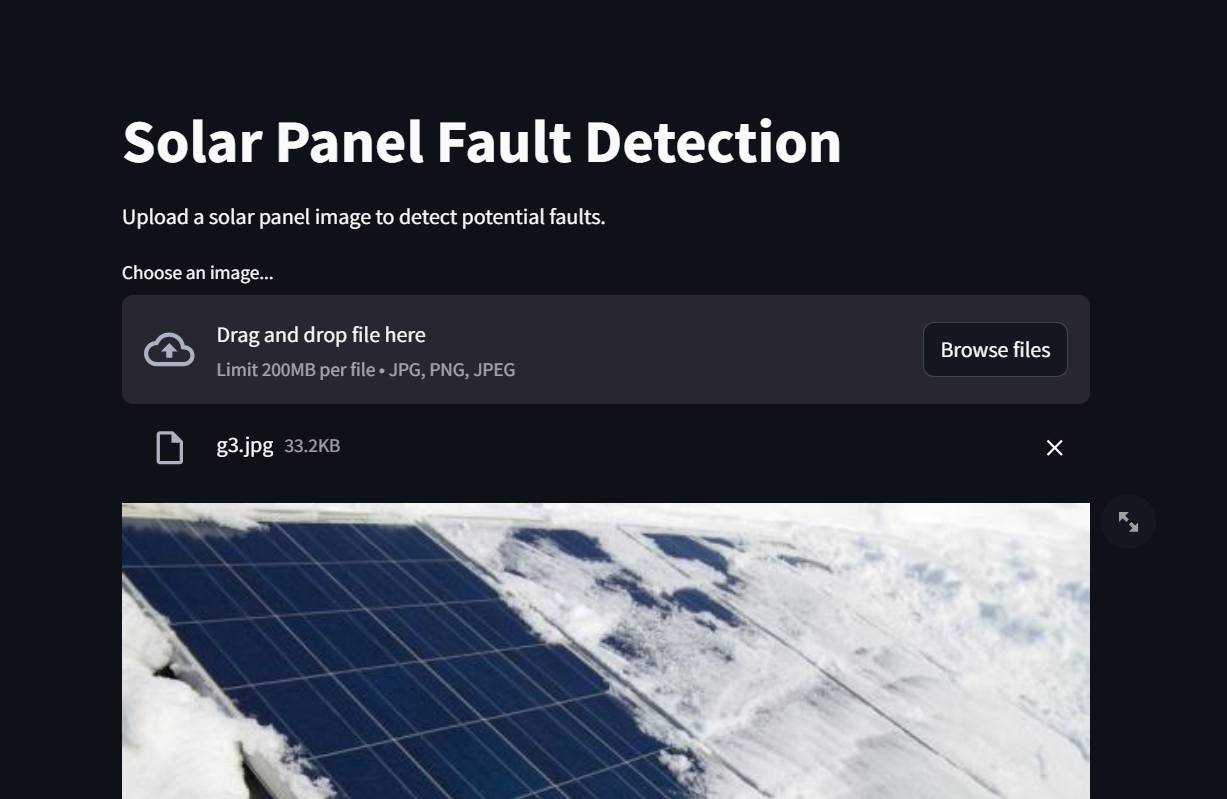
**Classification Report:**  
To evaluate the model's performance, we generated a classification report highlighting essential metrics such as accuracy, precision, recall, and F1-score for each fault category. This report illustrates the effectiveness of the model across categories like "Dust Accumulation," "Bird Droppings," "Snow Covered," "Clean," and "Electrical Damage." The report showcases the model's ability to distinguish between these faults accurately, providing clear insights into its strengths and areas for future improvements.



**Testing Performance:**  
In the testing phase, the model was tested rigorously on a separate dataset to ensure robustness and reliability. The results demonstrated the model's consistent performance with high accuracy across diverse images, confirming its generalization capability. This phase involved testing under various conditions, such as changes in lighting, image quality, and angle. Such rigorous testing ensures that the model can deliver accurate predictions in real-world scenarios, aiding solar farm operators in identifying issues swiftly.

**User-Friendly Dashboard Interface:**  
One of the project’s standout features is a web-based dashboard that allows users to upload images for fault detection easily. This interface was designed with accessibility in mind, requiring no technical expertise from users. With a single image upload, the dashboard processes the image through the model, which then classifies the fault type and displays the result along with a confidence score, aiding users in making informed maintenance decisions. This user-friendly design bridges the gap between complex AI models and practical application, bringing the technology closer to everyday use in solar maintenance.

This comprehensive output aligns with the project objectives of enhancing solar panel maintenance and reliability, ultimately supporting clean energy initiatives. The project represents a significant step toward efficient and effective solar panel management by leveraging AI-driven fault detection.

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Chapter 3:

Conclusion of the project-

In conclusion, this project demonstrates the potential of machine learning to transform solar panel maintenance by providing an automated, image-based fault detection system. Through extensive data collection, model training, and integration, the project successfully addresses key issues faced by solar energy systems, including the detection of common faults like dust, bird droppings, snow cover, and electrical damage. These faults often go undetected with traditional manual inspection, leading to decreased energy output and increased maintenance costs. By automating the detection process, this solution not only reduces operational costs but also enhances solar panel efficiency, ensuring maximum energy output and extending the lifespan of solar installations.

The implementation of a Convolutional Neural Network (CNN) model tailored for image classification allows for precise and reliable identification of fault categories. The system's ability to deliver real-time results supports prompt maintenance actions, making it especially beneficial for large-scale solar farms and remote installations. Furthermore, this project aligns with broader environmental goals, as improving the performance and reliability of solar panels contributes to the overall effectiveness of renewable energy sources.

Looking forward, this project opens up opportunities for further development, such as incorporating additional fault types and expanding the model for use in diverse weather conditions. The system’s design is also scalable, allowing for seamless integration with existing solar monitoring setups and future IoT advancements. In conclusion, this project highlights a significant step toward sustainable energy solutions, demonstrating how technology can enhance renewable energy infrastructure and contribute to a cleaner, more efficient future in energy production.

Project outlook :

This project provides a promising outlook on the future of AI-driven solar panel maintenance, setting a foundation for advanced automation in clean energy solutions. By leveraging machine learning for real-time fault detection, this solution offers significant potential to improve solar panel performance and longevity. The efficient identification of faults—such as dust accumulation, bird droppings, and electrical damage—reduces manual inspections and enhances preventative maintenance practices, which are crucial for large-scale solar farms and urban installations.

**Future Developments and Scaling:**  
Moving forward, expanding the dataset to include a broader range of environmental conditions, such as seasonal variations and regional weather impacts, could improve model accuracy even further. Integrating additional fault categories would also increase the system’s effectiveness. Additionally, implementing real-time data feeds from solar farms, paired with AI-driven insights, would enable predictive maintenance, allowing for even more proactive care and reduced downtime.

**Integration with IoT and Remote Monitoring:**  
With the rise of the Internet of Things (IoT), this project could evolve into a fully integrated system where IoT-enabled cameras continuously monitor solar installations. By coupling the fault detection model with IoT devices, operators could receive immediate alerts on detected issues, enabling swift intervention. This could be especially useful for remote or expansive solar farms where on-site monitoring is challenging.

**Environmental and Economic Impact:**  
The long-term benefits extend beyond operational efficiency. Proactive fault detection minimizes energy loss, directly contributing to the grid’s energy supply stability. This enhancement in solar panel output supports the reduction of greenhouse gas emissions by optimizing renewable energy sources. The cost savings in maintenance and the increased energy yield offer a compelling return on investment, highlighting the economic viability of this AI solution.

In conclusion, this project addresses current maintenance challenges while paving the way for AI-driven advancements in sustainable energy. As solar energy expands, AI-powered maintenance will be key to maximizing efficiency and supporting environmental objectives.

**ASSESSMENT**

**Internal:**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **SL NO** | **RUBRICS** | **FULL MARK** | **MARKS OBTAINED** | **REMARKS** |
| 1 | Understanding the relevance, scope and dimension of the project | 10 |  |  |
| 2 | Methodology | 10 |  |  |
| 3 | Quality of Analysis and Results | 10 |  |  |
| 4 | Interpretations and Conclusions | 10 |  |  |
| 5 | Report | 10 |  |  |
|  | **Total** | **50** |  |  |

**Date:**

**COURSE OUTCOME (COs) ATTAINMENT**

* **Expected Course Outcomes (COs):**

**(Refer to COs Statement in the Syllabus)**

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* **Course Outcome Attained:**

**How would you rate your learning of the subject based on the specified COs?**

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Description automatically generated with medium confidence](data:image/png;base64,iVBORw0KGgoAAAANSUhEUgAAAC4AAAAuCAMAAABgZ9sFAAAAAXNSR0IArs4c6QAAAARnQU1BAACxjwv8YQUAAABCUExURQAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAI7h9vIAAAAVdFJOUwABAgQJChgiPkNFa42msbS4yPn8/lhBRvcAAAAJcEhZcwAAIdUAACHVAQSctJ0AAACWSURBVEhL7cxJEsMgDABBsu9x1v9/NSANcVKFJPvOXASi7TR2eRvtAD/xYgbT2LlBcyyCwBN19VxuemuFEK+nQfZmir6njSydRGW/YEbBGGH3eVzgdh6/dt6oc6vOrTq3Km4/mZ/Urcp4snMqrPy2Tr9HZTIj/xqRnNwPzn+ES5jqtOYahM6xcINKR3ZmuLEDD42WkJQ+dFI6Wwc5N/kAAAAASUVORK5CYII=)![A black background with a black square

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**1 2 3 4 5 6 7 8 9 10**

**LOW HIGH**

* **Learning Gap (if any):**

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* **Books / Manuals Referred:**

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**Date: Signature of the Student**

* **Suggestions / Recommendations:**

**(By the Course Faculty)**

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**Date: Signature of the Faculty**

