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A Holistic Approach to Defect Detection in Solar Modules: Leveraging Lifecycle Data for Improved Performance

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Abstract—The efficient maintenance and optimization of solar modules are critical for sustaining high energy yields over their operational lifetimes. This research introduces a comprehensive system designed to enhance lifecycle traceability and defect detection in solar modules using a combination of advanced image analysis and machine learning techniques. By leveraging Convolutional Neural Networks (CNN), You Only Look Once (YOLO) object detection, and deep learning, the system analyzes thermal and normal imaging data as well as current-voltage (IV) characteristics and curves. The proposed framework enables the detection of common faults, such as hotspots, cell cracks, and degradation patterns, which can impact performance and safety. Integrated data management and tracking capabilities facilitate end-to-end lifecycle monitoring, providing accessible, organized insights for stakeholders involved in solar module maintenance and diagnostics. The model shows an accuracy of 90%. The results show that the system not only improves accuracy in fault identification but also allows efficient storage and retrieval of diagnostic data, presenting a robust solution for advancing photovoltaic asset management

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I. INTRODUCTION

As global reliance on renewable energy sources intensifies, photovoltaic (PV) solar panels have become pivotal in the transition towards sustainable energy. However, the efficiency of these solar modules can decline due to environmental stressors, operational issues, and inherent material degradation over time. Ensuring consistent performance and maximizing lifespan thus require effective and proactive maintenance strategies. Traditional manual inspection methods are often labor-intensive, costly, and may miss subtle indicators of potential failures, highlighting the need for automated and precise diagnostic solutions.

This paper proposes a novel system for lifecycle traceability and defect detection in solar modules by integrating computer vision and machine learning. Employing Convolutional Neural Networks (CNN) and the YOLO object detection algorithm, the system processes both thermal and visible spectrum images to detect faults such as hotspots, cracks, and discoloration. Additionally, IV characteristics and their corresponding curves are analyzed to provide a more holistic view of module health. By embedding deep learning techniques into a structured data management framework, the system allows for seamless data tracking, storage, and retrieval, thus enabling stakeholders to access valuable insights across the PV lifecycle.

Our paper aims to address key challenges in solar module maintenance, such as the need for real-time, accurate fault detection and lifecycle data accessibility, to support informed decision-making and predictive maintenance. Through this work, we demonstrate the potential of integrating state-of-the-art image analysis and data management within the solar energy sector, driving improvements in efficiency, reliability, and safety of photovoltaic systems.

II. BACKGROUND

➢ *System Overview*

The proposed system integrates advanced defect detection and data traceability throughout the solar module lifecycle. It employs deep learning (DL) techniques for accurate and real-time defect identification during manufacturing and field operations. Data from various stages is captured, securely stored, and linked to individual modules through unique identifiers. DL-based predictive analytics enhances fault prediction and maintenance planning. The system ensures efficient traceability, quality control, and long-term performance monitoring of solar modules. This comprehensive approach optimizes lifecycle management

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and operational efficiency.

- *Backend Architecture*

The backend of the solar panel defect detection system ensures seamless coordination of deep learning models and data processing components. It starts with image acquisition from thermal and visible spectrum cameras, followed by preprocessing to enhance defect detection accuracy. Convolutional Neural Networks (CNNs) and YOLO algorithms analyze these images to identify defects like hotspots, cracks, and discoloration. Additionally, IV curve analysis correlates electrical performance with detected faults for a comprehensive assessment. All data is stored in a structured database, ensuring easy traceability throughout the module's lifecycle. A user-friendly interface provides real-time defect reports and predictive analytics, enabling proactive maintenance. Automated alerts notify operators of critical issues, optimizing efficiency and ensuring long-term solar panel reliability.

- *Client Side Interface*

The client-side interface of the solar panel defect detection system is designed for seamless user interaction with role-based access control for Inspectors, Admins, and Super Admins. Inspectors can upload images, view detected defects, and generate reports based on real-time analysis. Admins oversee system operations, manage data, and validate defect reports, ensuring accurate tracking of module health. Super Admins have full control, including user management, access permissions, and system configuration. The interface provides a dashboard with real-time defect insights, historical data, and predictive analytics. Secure authentication and access control ensure data integrity while enabling stakeholders to make informed maintenance decisions efficiently.

III. RELATED WORK

Several research works have played an important role in shaping the development of intelligent parking systems. In the paper [10] the authors provide an in-depth review of the protection challenges and fault diagnosis methods in photovoltaic (PV) systems. It examines various types of faults that can occur in solar power setups, including line-to-line faults, ground faults, and open-circuit issues, and highlights the potential hazards and energy losses associated with undetected faults. The authors discuss both traditional and modern diagnostic techniques, ranging from current-voltage (I-V) curve analysis and infrared thermography to advanced machine learning and artificial intelligence approaches. The review emphasizes the need for reliable and automated fault detection mechanisms to ensure the safety, efficiency, and longevity of PV systems. The paper also identifies gaps in existing fault diagnosis technologies and suggests directions for future research, making it a valuable resource for those developing innovative monitoring and protection solutions in the solar energy sector.

In this study *[2] t*he authors present a machine vision system tailored for detecting edge defects in photovoltaic (PV) glass. They enhance the SqueezeNet architecture to improve feature extraction capabilities, enabling the accurate identification of defects such as cracks and chips. The system incorporates high-contrast imaging solutions to capture detailed visuals of the glass edges, which are then processed by the improved SqueezeNet model. Experimental results demonstrate that this approach achieves high accuracy in defect detection while maintaining computational efficiency, making it suitable for real-time industrial applications.

In this study titled **[6],**the authors explore the integration of thermal imaging and artificial intelligence (AI) to enhance the detection of defects in solar panels. They propose a system that utilizes infrared cameras to capture thermal images of photovoltaic modules, identifying anomalies such as hotspots, cracks, and faulty cells. These thermal images are processed using advanced AI algorithms, including convolutional neural networks (CNNs), to accurately classify and localize defects. The research demonstrates that combining thermal imaging with AI not only improves the precision of defect detection but also enables real-time monitoring, thereby reducing maintenance costs and enhancing the efficiency of solar energy systems. The study's findings suggest that this integrated approach is a viable solution for automated, efficient, and cost-effective maintenance of photovoltaic installations.

Table 1 Literature Review

Paper	Dataset	Objective	Methodology	Result	Challenges
Abdelsattar, Montaser, et al. (2025)	Solar cell image dataset	Automated defect detection in solar cells	Deep learning algorithms (CNNs) for image classification	High accuracy in detecting defects	Dataset limitations, computational complexity
Laguna, G., et al. (2024)	Minimal data from PV systems	Detecting abnormal PV system operations	Recursive Least Squares (RLS) algorithms	Reliable fault detection with minimal data	Scalability, adaptability to different PV configurations
Rajeshkanna, R., et al. (2024)	Real-time solar panel manufacturing data	Fault-related feature discrimination in cell partitioning and defect classification	Custom deep learning network for defect identification	Improved accuracy in defect detection	Real-time processing challenges, hardware requirements
Xiong, J., et al. (2024)	PV glass edge images	Defect detection in PV glass edges	Improved SqueezeNet-based classification	Enhanced detection accuracy with optimized model	Limited dataset, edge case handling

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Joshua, S. R., et al. (2024)	Solar-hydrogen system data	Advanced fault detection in solar-hydrogen systems	Convolutional Neural Networks (CNN) applied to fault detection	High fault detection rate in hybrid energy systems	Integration with different PV systems, false positives
Ramadan, E. A., et al. (2024)	Photovoltaic module data	Fault detection and classification using transformer neural networks	Transformer-based deep learning model	Enhanced accuracy over traditional CNNs	High computational cost, data preprocessing challenges
Umar, S., et al. (2024)	Thermal imaging data	AI-based defect identification in solar panels	Combination of AI and thermal imaging for defect detection	Improved detection efficiency	Cost of thermal imaging equipment, data variability
Giovanardi, Matteo, et al. (2023)	IoT-enabled life-cycle data	Enabling circular economy via lifecycle information flows	Theoretical IoT framework for building façade traceability	Improved traceability and sustainability insights	Implementation complexity, data security concerns
Abdelsattar, Montaser, et al. (2025)	Solar cell image dataset	Automated defect detection in solar cells	Deep learning-based image analysis	High detection accuracy	Large-scale deployment challenges
Pillai, Dhanup S., et al. (2018)	Various PV system fault datasets	Comprehensive review of PV system protection and fault diagnosis	Literature review on fault diagnosis methods	Identified key challenges and research gaps	Lack of standard datasets, evolving PV technologies

IV. PROPOSED SYSTEM

➢ *System Overview*

The proposed solar panel defect detection and data traceability system leverages deep learning techniques to automate fault identification and lifecycle management. It integrates high-resolution thermal and visible spectrum imaging, coupled with advanced Convolutional Neural Networks (CNNs) and the YOLO object detection algorithm, to detect defects such as hotspots, cracks, and discoloration. Additionally, IV curve analysis enhances the accuracy of fault diagnostics by correlating electrical performance with detected defects. This multi-layered approach ensures comprehensive monitoring and early fault detection, significantly improving the efficiency and reliability of solar panels.

The backend infrastructure plays a crucial role in processing, storing, and managing defect detection data. It ensures real-time synchronization of module performance records, enabling seamless tracking throughout the solar panel lifecycle. A structured database organizes detected faults, IV characteristics, and maintenance history, allowing efficient retrieval for predictive analytics and decision-making. Automated alerts notify operators of critical defects, reducing downtime and optimizing maintenance schedules, ultimately leading to cost savings and enhanced energy output.

The client-side interface is designed with role-based access control to facilitate seamless interaction for different stakeholders. Inspectors can upload images, view defect reports, and generate insights, while Admins manage data validation and system operations. Super Admins oversee user management, system configurations, and access permissions, ensuring secure and structured data governance. The interactive dashboard provides real-time insights, historical trends, and predictive analytics, empowering stakeholders with data-driven decision-making for improved solar panel maintenance and lifecycle management.

➢ *System Architecture*

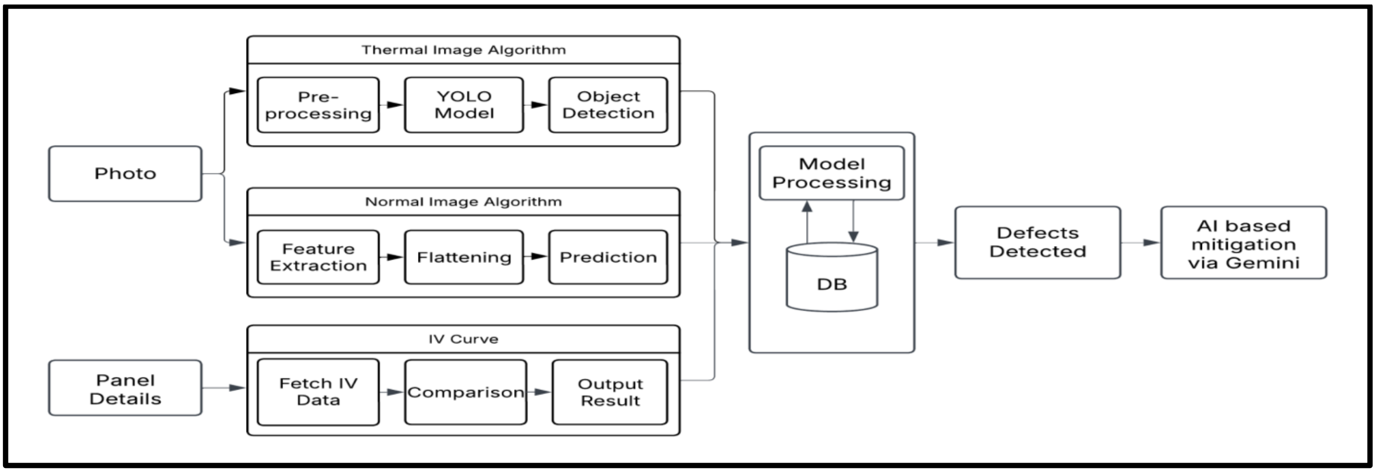

Fig 1 System Architecture

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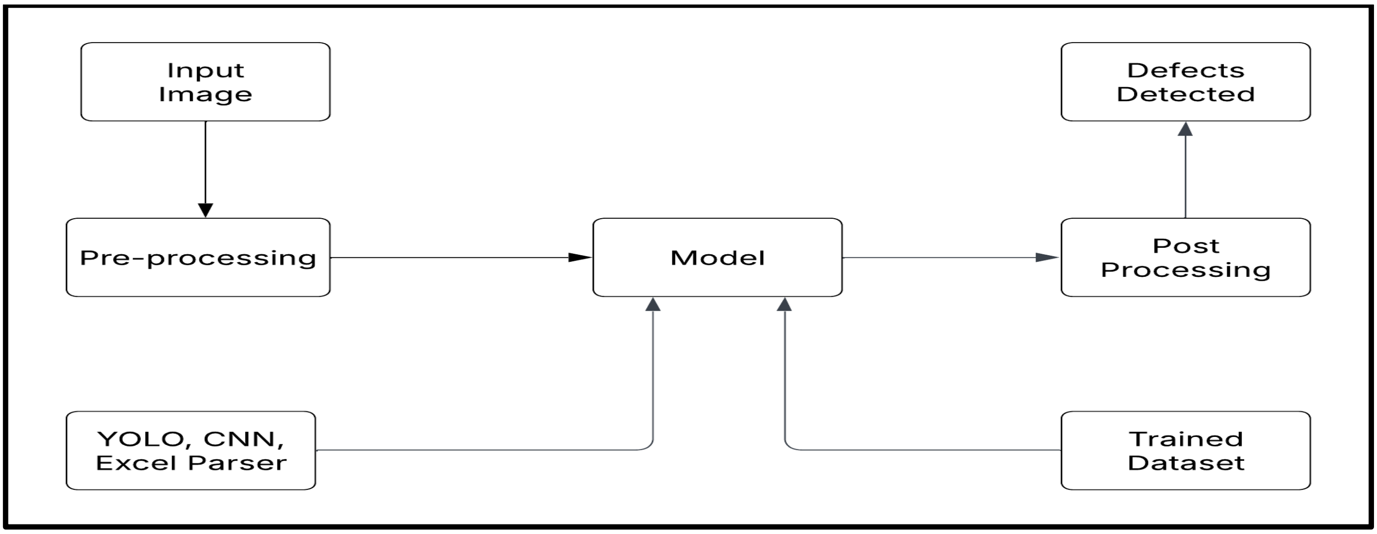

Fig 2 Defect Detection Process Flow

➢ *Defect Detection Using Normal Images*

Defect detection using normal (visible spectrum) images is a crucial approach in identifying faults in solar panels. High-resolution cameras capture images under natural lighting conditions, enabling the detection of surface-level defects such as cracks, discoloration, delamination, dirt accumulation, and broken glass. These images are then processed using computer vision and deep learning techniques to enhance fault detection accuracy and automate the inspection process.

- *Data Gathering*

✓ *Capturing High-Resolution Images:*

Standard cameras are used to capture visible-spectrum images of solar panels under natural lighting conditions.

✓ *Varied Environmental Conditions:*

Images are collected at different times of the day and under diverse weather conditions to account for variations in lighting and panel appearances.

✓ *Image Annotation:*

Each image is classified to indicate defects such as cracks, discoloration, dirt accumulation, delamination, or broken glass. Proper annotation is essential for training an accurate machine learning model.

- *Preprocessing*

✓ *Image Enhancement:*

Techniques such as contrast adjustment, edge detection, and noise reduction improve the clarity of defects, making them easier for the model to detect.

✓ *Data Augmentation:*

Various transformations increase dataset diversity and improve the model's robustness:

▪ Rotation: Simulates different camera angles and perspectives.
▪ Scaling: Represents solar panels at different distances.
▪ Flipping: Ensures defect recognition from multiple orientations.
▪ Brightness & Contrast Adjustments: Compensates for variations in lighting conditions.

- *Model Training*

✓ *CNN Model Selection:*

A Convolutional Neural Network (CNN), VGG16 is selected for defect detection.

✓ *Configuring Model Parameters:*

Learning rate, batch size, and training epochs are optimized for performance.

✓ *Training with Annotated Data:*

The labeled dataset is used to train the model, enabling it to recognize and classify different surface defects in solar panels.

- *Defect Detection*

✓ *Deploying the CNN Model:*

The trained model is implemented for real-time analysis of incoming images.

✓ *Automated Defect Identification:*

The system scans images to detect and classify faults, distinguishing between different defect types.

This method offers a cost-effective, non-invasive, and scalable solution for monitoring solar panel health. By integrating defect detection with a structured database, inspection history can be stored and analyzed over time, enabling predictive maintenance. While normal image-based detection is effective for surface-level faults, combining it with infrared thermal imaging and electrical performance analysis further enhances the accuracy and reliability of defect identification capabilities and demonstrates the seamless, automated and unattended nature of our smart parking solution.

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➢ *Defect Detection Using Thermal Images*

- *Data Gathering*

✓ *Capturing Thermal Images:*
Inspectors use infrared cameras to acquire thermal images of solar panels.

✓ *Varied Conditions:*
Images are collected at different times and environmental conditions to ensure a diverse dataset covering multiple panel states.

✓ *Image Annotation:*
Each image is labeled to indicate observable defect types such as hotspots, cracks, or faulty cells. This step is crucial for training the machine learning model to recognize patterns effectively.

- *Preprocessing*
Enhancing Clarity & Contrast: Image processing techniques improve visibility and definition of defects, making them more distinguishable for the model.

✓ Data Augmentation:
Various transformations are applied to increase dataset diversity and improve model robustness:

- **Rotation:** Simulates different viewing angles.
- **Scaling:** Represents panels at varying distances.
- **Flipping:** Ensures the model can recognize defects in different orientations.

- *Model Training*
YOLO Model Selection: A suitable YOLO model version (e.g., YOLOv9) is chosen for defect detection. Configuring Model Parameters: Key parameters like learning rate, batch size, and detection thresholds are set. Training with Annotated Data: The preprocessed images, along with their annotations, are used to train the model for precise defect identification.

- *Defect Detection*
Deploying the YOLO Model: The trained model is implemented for real-time defect detection. Real-Time Analysis: Incoming images are analyzed to identify potential defects. Defect Classification: The model categorizes detected defects based on their type, such as hotspots, cracks, or faulty cells. Displaying Results: Bounding boxes and labels are overlaid on images, highlighting defect areas. These results are accessible to relevant users, including admins and inspectors.

➢ *Defect Detection using IV analysis*

Solar energy adoption is growing exponentially, but module defects (e.g., microcracks, PID, hot spots) cause 15–25% annual efficiency losses. Traditional defect detection methods (e.g., electroluminescence, thermal imaging) are costly, time-consuming, and lack predictive capabilities.

- *IV Curve Fundamentals*

✓ Isc (Short-Circuit Current): Induces shading, soiling, or cell cracks.
✓ Voc (Open-Circuit Voltage): Reflects PID or diode failures.
✓ Pmax (Maximum Power): Key indicator of overall health.
✓ Fill Factor (FF): Sensitive to series/shunt resistance defects.

- *AI-Driven Defect Detection Framework*
Various parameters are measured from portable IV tracers such as Pnom, Isc, Voc, M_eff%, FF, Imp, Vmp, etc. The dynamic thresholds for each parameter are adjusted for environmental conditions. As an input the IV parameters and environmental data is taken and with help of spatial-temporal pattern recognition, the output is generated which includes defect type and severity score.

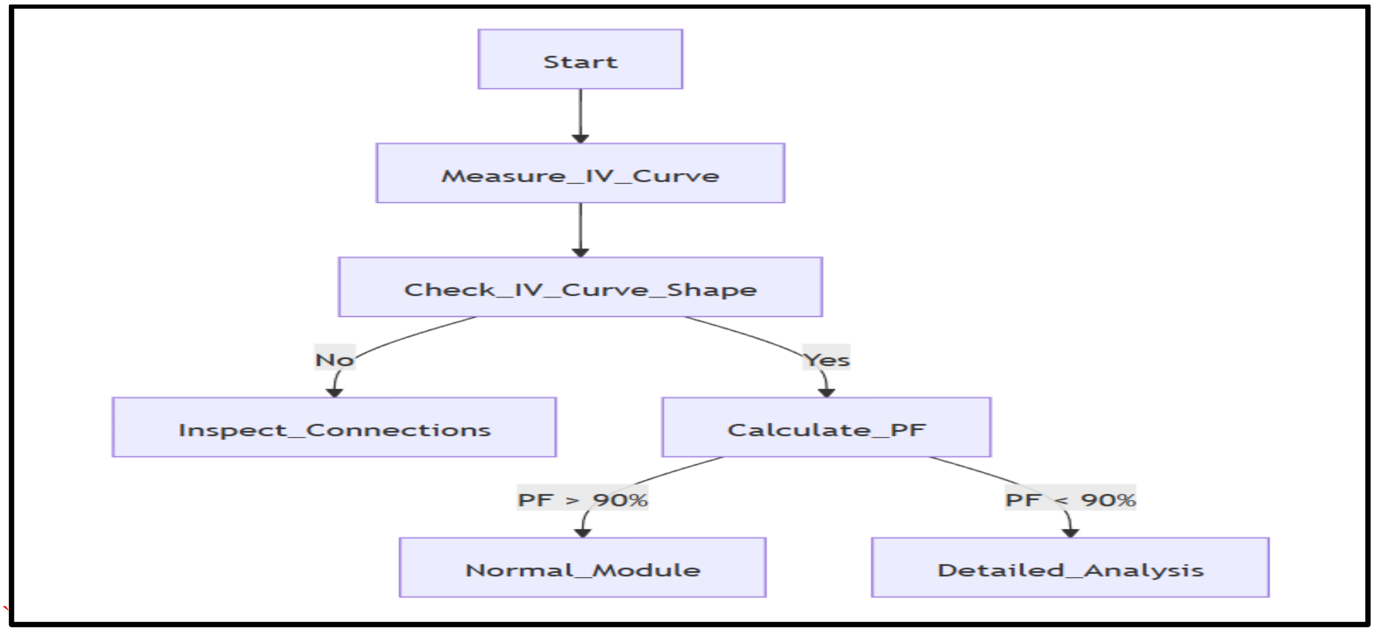

Fig 3 Algorithm of Workflow

➢ *Use of MongoDB for Storage*

MongoDB plays a key role in storing and managing defect detection and lifecycle traceability data for solar panels. As a NoSQL database, it efficiently handles unstructured data like high-resolution images, defect reports, IV curve data, and maintenance history. Its document-based structure allows seamless storage of module-specific details, including timestamps, location, defect classifications, and performance metrics.

The system leverages MongoDB's real-time data processing to store defect detection results from deep learning models, linking each solar panel's inspection records, faults, and predictive analytics. Indexing and query optimization enable fast data retrieval, improving maintenance decisions. Its horizontal scalability supports large-scale solar farms without performance loss.

MongoDB's role-based access control (RBAC) enhances security by restricting data access for roles like Inspectors and Admins. Real-time synchronization ensures up-to-date information, while replication and backup provide fault tolerance. Integrating MongoDB ensures efficient storage, quick retrieval, and seamless lifecycle management, boosting defect detection and predictive maintenance.

➢ *Innovation*

This project introduces a novel approach to solar panel defect detection and lifecycle traceability by integrating deep learning, computer vision, and structured data management. Unlike traditional manual inspection methods, which are labor-intensive and prone to human error, this system automates fault detection using Convolutional Neural Networks (CNNs) and the YOLO object detection algorithm. By analyzing both normal (visible spectrum) and thermal images, the system accurately identifies defects such as cracks, discoloration, and hotspots in real-time, significantly improving inspection efficiency and accuracy.

A key innovation lies in the seamless combination of defect detection with a robust data traceability framework. Using MongoDB as the backend database, the system ensures efficient storage, retrieval, and tracking of inspection records, IV curve analysis, and maintenance history. Each solar panel is assigned a unique identifier, allowing stakeholders to monitor its performance throughout its lifecycle. Predictive analytics further enhance the system by forecasting potential failures, enabling proactive maintenance and reducing operational costs.

Additionally, the project incorporates a role-based access control system, ensuring secure and structured data governance. Inspectors can upload images and view reports, Admins can manage defect validation, and Super Admins have full system control. The interactive dashboard provides real-time insights and historical trends, making data-driven decision-making more accessible. By integrating deep learning, real-time defect detection, and intelligent data management, this project represents a significant advancement in solar panel monitoring, enhancing reliability, efficiency, and sustainability in renewable energy systems.

➢ *System Configuration*

The system configuration for solar panel defect detection consists of both hardware and software components optimized for efficient deep learning-based analysis. The hardware setup includes high-resolution infrared and visible spectrum cameras for capturing detailed images of solar panels under varying environmental conditions. A GPU-enabled computing system, such as one equipped with NVIDIA CUDA-compatible GPUs, is essential for processing deep learning models efficiently. Additionally, a cloud-based or on-premise server is used for data storage and real-time analysis, ensuring seamless accessibility for stakeholders.

On the software side, the system utilizes Python-based frameworks, including TensorFlow and PyTorch, for deep learning model development. The YOLO object detection algorithm is implemented to detect and classify defects with high accuracy. MongoDB serves as the backend database for storing inspection data, defect records, and lifecycle information. A web-based dashboard with role-based access control allows Inspectors, Admins, and Super Admins to interact with the system, view defect reports, and manage solar panel maintenance schedules. The integration of automated alerts and predictive analytics enhances decision-making, making the system highly efficient and scalable.

V. PROOF OF WORK

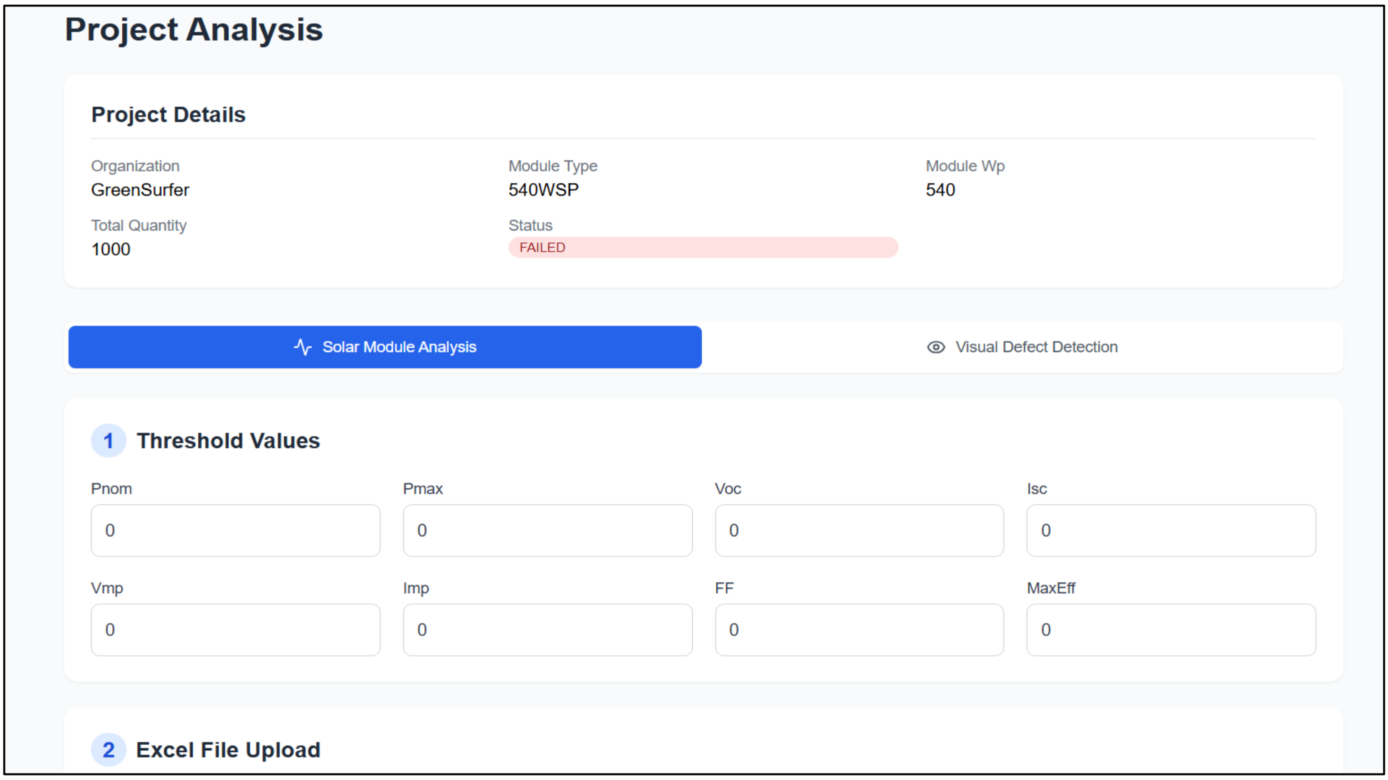

Fig 4 IV Analysis page(i)

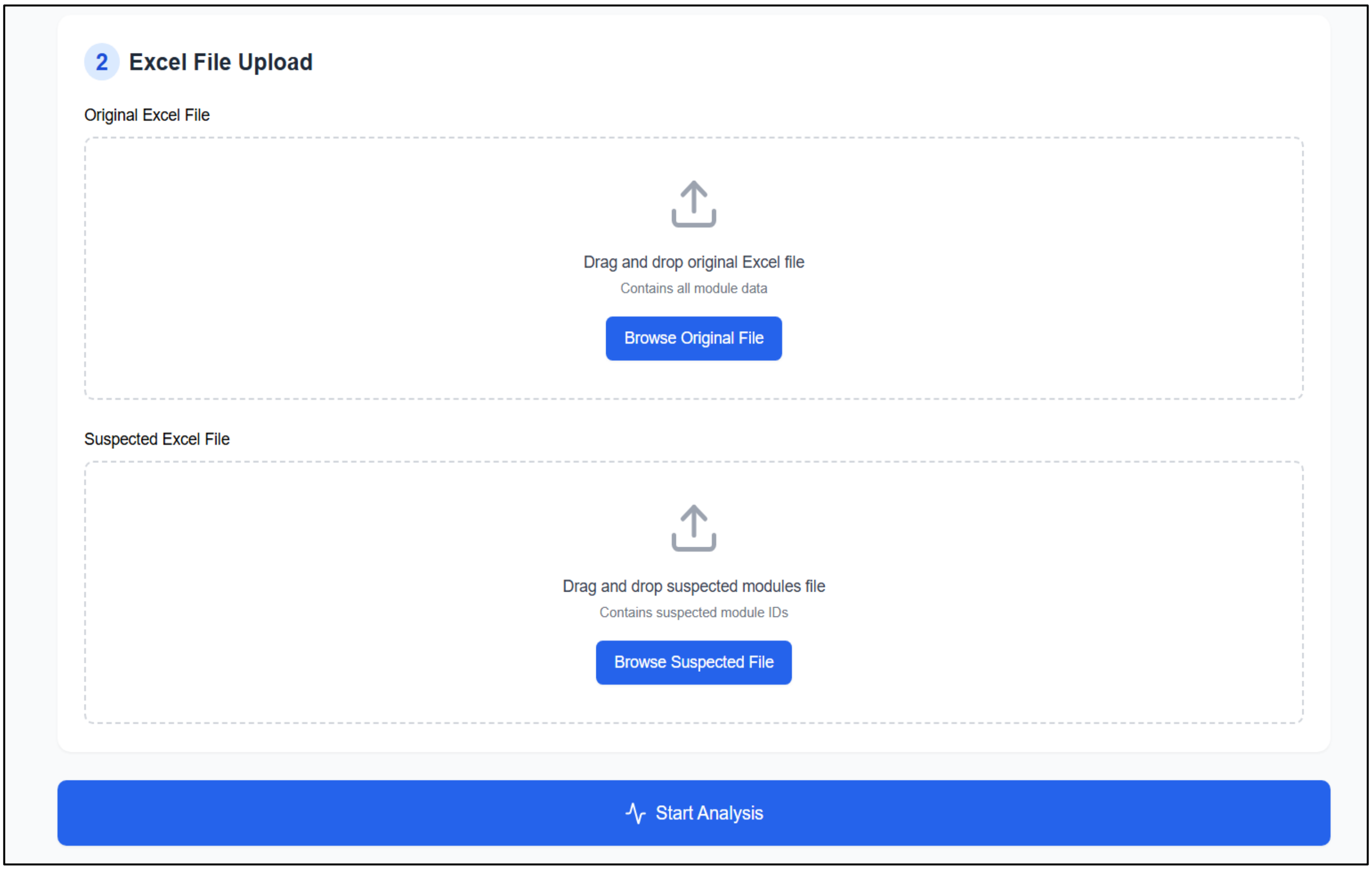

Fig 5 IV-Analysis Page(ii)

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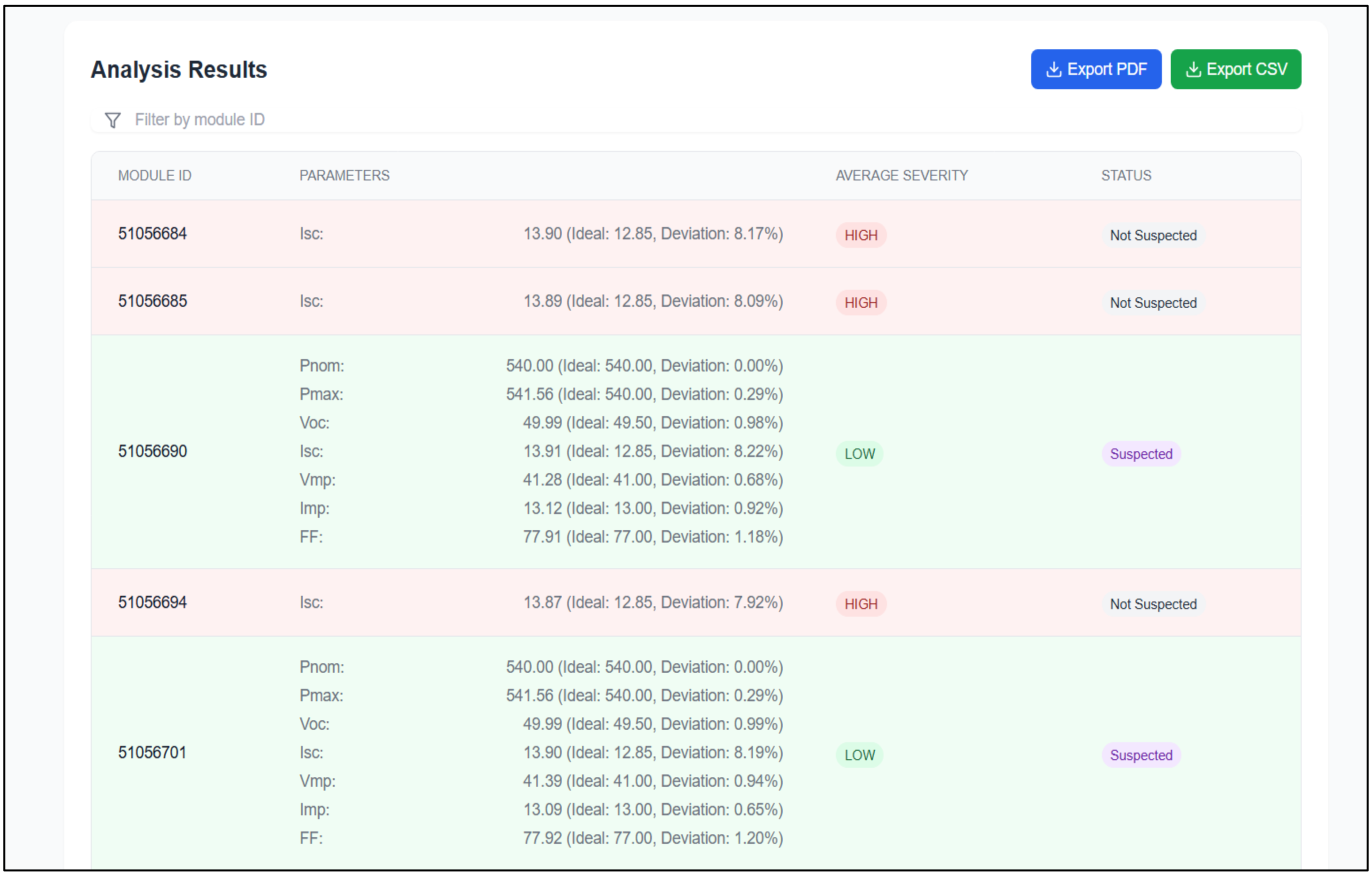

Fig 6 IV-Analysis Result Page

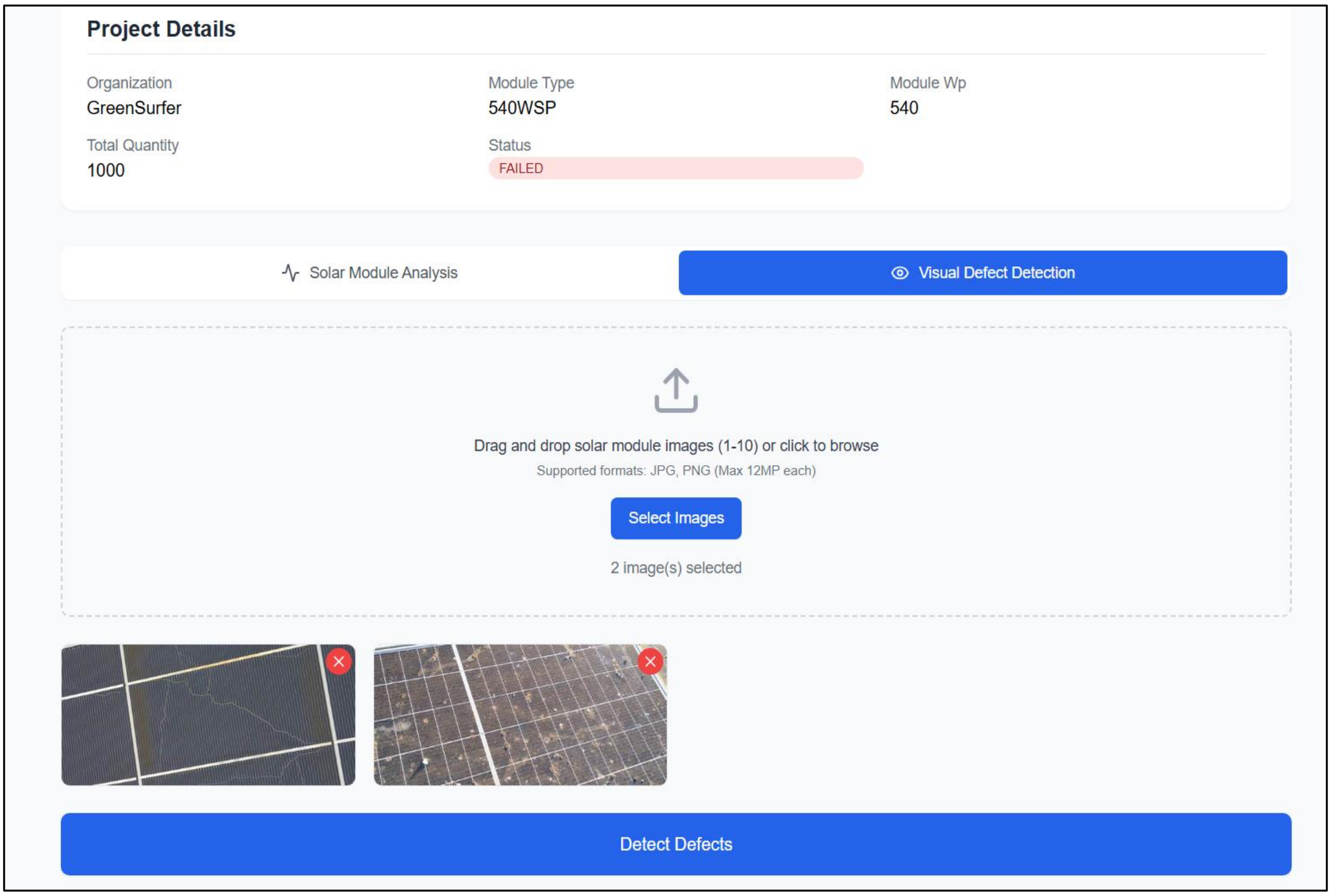

Fig 7 Visual Image Analysis page(i)

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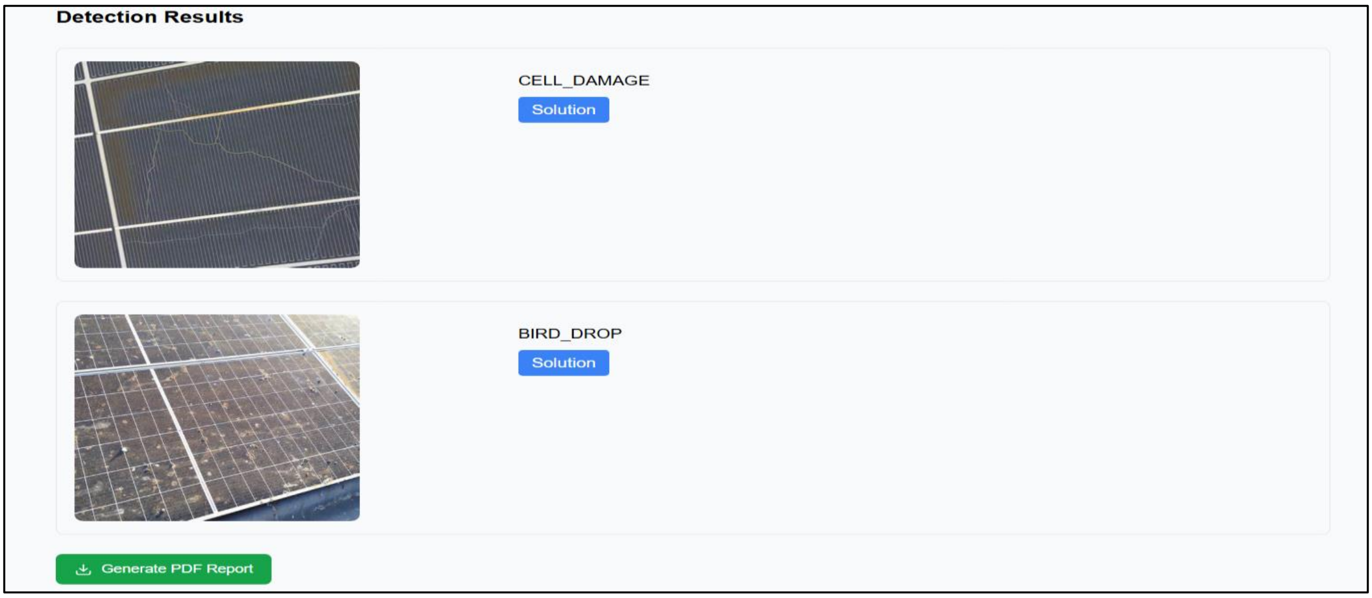

Fig 8 Visual Image Analysis page(ii)

```
epoch = 15
history = model.fit(train_ds, validation_data=val_ds, epochs=epoch,
    callbacks = [
        tf.keras.callbacks.EarlyStopping(
            monitor="val_loss",
            min_delta=1e-2,
            patience=3,
            verbose=1,
        )
    ]
)

model.save("img_fault.h5")
```

```
Epoch 1/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 774s 35s/step - accuracy: 0.2307 - loss: 5.4950 - val_accuracy: 0.4629 - val_loss: 1.7415
Epoch 2/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 791s 35s/step - accuracy: 0.6136 - loss: 1.3598 - val_accuracy: 0.6971 - val_loss: 1.1335
Epoch 3/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 800s 35s/step - accuracy: 0.7616 - loss: 0.7316 - val_accuracy: 0.7371 - val_loss: 0.8995
Epoch 4/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 799s 35s/step - accuracy: 0.8883 - loss: 0.3678 - val_accuracy: 0.7657 - val_loss: 0.8514
Epoch 5/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 802s 35s/step - accuracy: 0.9278 - loss: 0.2266 - val_accuracy: 0.7771 - val_loss: 0.6736
Epoch 6/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 788s 34s/step - accuracy: 0.9487 - loss: 0.1329 - val_accuracy: 0.7829 - val_loss: 0.8111
Epoch 7/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 818s 35s/step - accuracy: 0.9439 - loss: 0.1607 - val_accuracy: 0.7829 - val_loss: 0.8532
Epoch 8/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 801s 35s/step - accuracy: 0.9803 - loss: 0.0692 - val_accuracy: 0.7943 - val_loss: 0.8213
Epoch 8: early stopping
```

Fig 9 Model Implementation

VI. CONCLUSION

This research paper presents an innovative system for defect detection and data traceability throughout the solar module lifecycle. By leveraging deep learning for defect identification, the system ensures precise real-time monitoring, reducing reliance on manual inspections and minimizing operational costs. Automated processes enhance efficiency, improving the quality and reliability of solar modules while enabling predictive maintenance and reducing downtime. Manufacturers benefit from increased production accuracy, while operators can maximize energy output and ensure long-term performance.

Beyond defect detection, the system incorporates advanced data traceability, enabling seamless tracking of module history, performance, and maintenance activities. This data-driven approach optimizes manufacturing processes, enhances lifecycle management, and improves decision-making for stakeholders. By offering automated defect detection, robust traceability, and actionable insights, this system advances intelligent solar module management, contributing to greater efficiency, reliability, and sustainability in the solar energy sector.

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