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INTELLIGENT IIOT-DRIVEN THERMAL HEAT ANALYSIS FOR FAULT DETECTION IN SOLAR PV ARRAYS

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ABSTRACT

The global installed capacity of Solar Photovoltaic (PV) systems surpassed 1.6 TW in 2024, with an expected annual growth rate of 12% over the next five years. However, environmental factors such as bird droppings, dust accumulation, snow coverage, and structural damages significantly reduce energy yield and lifespan of PV modules. Existing manual inspection methods are time-consuming, error-prone, and unable to provide real-time analysis for large-scale solar farms. To address these challenges, this study proposes an Intelligent IIoT-Driven Thermal Heat Analysis framework for automated fault detection in Solar PV arrays. The system integrates IIoT-based real-time data acquisition from both visual and thermal imaging sensors, followed by advanced image preprocessing techniques including noise reduction, contrast enhancement, and adaptive resizing to standardize diverse input sources. Thermal heat maps are analyzed to identify abnormal temperature variations indicative of faults such as hot spots and localized heating. While existing K-Nearest Neighbour (KNN) and Random Forest Classifier (RFC) models are used as benchmarks, the core novelty lies in the proposed hybrid VGG19 with Deep Neural Network (DNN) architecture, enabling deep feature extraction from both visible and thermal channels. The extracted features are fused and classified into six distinct fault categories: Bird-Drop, Clean, Dusty, Electrical Damage, Physical Damage, and Snow-Covered.

1. INTRODUCTION

The solar energy revolution is accelerating at a remarkable pace. By the end of 2024, global solar photovoltaic (PV) capacity had surpassed 2.2 terawatts [1], with over 600 GW added in that single year. Furthermore, renewables contributed nearly half of all newly installed power generation capacity in 2024 [2], reaffirming solar's dominant role in the clean energy transition as shown in Figure 1. This extraordinary growth underscores not only the technological feasibility of solar power but also its central position in global energy strategies.

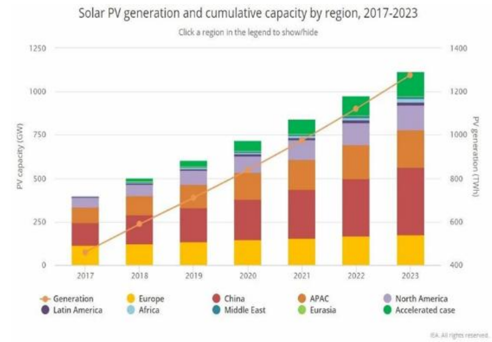

Figure 1: Statistical graph of solar PV generation.

Despite this transformative adoption, PV system performance faces persistent challenges driven by soiling dust, snow, bird droppings, and other surface contaminants [3]. Soiling is the most influential factor affecting system yield after the primary variable of irradiance, causing annual energy production losses of 3–5% globally, translating into economic losses on the order of several billion euros [4]. In extreme cases, bird droppings alone have been found to reduce panel efficiency by up to 43%, while inducing thermal "hot spots" and raising surface temperature by about 5% compared to clean modules. These performance degradations

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jeopardize both the operational viability and financial return of solar PV installations particularly as they scale and become integral to energy infrastructure [5]. In arid and dusty environments, the lack of natural precipitation exacerbates soiling, leading to accelerated yield degradation and increased maintenance costs. Moreover, current manual or periodic cleaning strategies are often insufficiently precise and cost-effective, highlighting the urgent need for smarter, data-driven methods to detect and mitigate faults especially across complex and large-scale solar farms.

2. LITERATURE SURVEY

Karakan, A., et al. [6] proposed a deep learning approach to detect and classify faults in solar panel cells using electroluminescence (EL) imaging. They created a custom dataset of monocrystalline and polycrystalline solar cell images with intact, cracked, and broken labels. They balanced the dataset using data augmentation and tested seven architectures. SqueezeNet yielded 97.82 % accuracy on monocrystalline and 96.29 % on polycrystalline cells. They achieved rapid fault detection. Ghahremani, A., et al. [7] introduced an AI-driven framework for detection and localization of solar panel defects, emphasizing machine learning algorithms and advanced engineering informatics. They applied feature selection techniques within supervised learning architectures to identify defects effectively. The method provided structured localization of faults across panel imagery. It leveraged both detection and localization capabilities for real-world applicability. Matusz-Kalász, D., et al. [8] presented an overview of CNN-based image analysis in solar cells, photovoltaic modules, and power plants. They surveyed diverse CNN models applied to PV imagery across multiple scales—cells, modules, installations. They compared model performance metrics, architectural trends, and feature hierarchy extraction within different applications. They structured knowledge across model families for practitioners.

Sufian, R., et al. [9] addressed solar panel fault detection and classification using transfer learning and DNN frameworks. They applied pre-trained networks fine-tuned on PV fault imagery to improve classification accuracy. They exploited learned representations from large-scale datasets to enhance performance on fault types. They demonstrated efficient transfer of knowledge with few adjustments. Abdelsattar, M., et al. [10] conducted automated defect detection in solar cell images via extensive testing of 24 distinct CNN architectures including ResNet, DenseNet, VGG, Inception, MobileNet, Xception, SqueezeNet, and AlexNet. They evaluated performance across a balanced dataset of 3,102 solar cell images. MobileNetV2 achieved 99.95 % and Xception achieved 99.29 % accuracy with minimal validation loss. They demonstrated lightweight model viability in resource-constrained contexts Rohith G., et al. [11] proposed SparkNet, a deep learning model built with Fire Modules combining Squeeze and Expand layers—for surface fault detection (shading, cracking, contaminants) in solar panels. They trained the model on a diverse dataset under varying environmental conditions and achieved approximately 95 % across accuracy, precision, recall, and F1 measures.

Et-taleby, A., et al. [12] introduced a hybrid detection framework using a thermal image pipeline combined with fuzzy logic classification to identify and grade faults in photovoltaic systems. The method fused thermal clustering with fuzzy logic but did not incorporate deep feature extraction or structured selection to enhance classification of subtle defect gradations. Abraheem, S., et al. [13] presented an advanced fault detection system by merging VGG19 for hierarchical feature extraction with the Jellyfish Optimization Search Algorithm (JFOSA) to optimize feature selection, yielding 98.34 % accuracy, 98.71 % sensitivity, 98.69 % specificity, and 94.03 % AUC. Despite high performance, the optimization technique introduced significant computational overhead, reducing real-time applicability in edge deployments. Prasshanth, C. V., et al. [14] employed unmanned aerial vehicle (UAV) imagery coupled with rough set theory to detect PV system faults from captured images. The method positioned rough set classification for non-probabilistic pattern analysis. The deployment relied on simplistic feature granularity and lacked refined feature extraction, resulting in limited classification precision across complex fault categories. Jack, K. E., et al. [15] developed a convolutional neural network (CNN) tailored for solar panel fault detection, integrating preventive maintenance reporting functionality. While offering a full detection-to-report pipeline, the CNN structure lacked advanced feature selection strategies, limiting its capacity to differentiate subtle anomaly variations.

Gasparyan, H., et al. [16] proposed a lightweight neural network architecture for classifying solar panel faults using both electroluminescence (EL) and RGB images. They crafted efficient convolutional modules to process dual-domain inputs, aiming to balance accuracy with computational demand. The model demonstrated strong classification performance with a reduced parameter footprint and suitability for real-time deployment. It achieved reliable differentiation between internal defects and surface-level anomalies. Manimegalai, V., et al. [17] integrated Generative Adversarial Networks (GANs) with ResNet for solar panel fault detection. The GAN component enriched the dataset by generating synthetic images that improved class balance, while ResNet extracted hierarchical features for classification. This synergistic design delivered improved detection rates, especially for underrepresented defect categories. It enhanced robustness of the deep model under limited data scenarios. Feature selection relied solely on ResNet's hierarchical layers without optimizing or pruning for defect-specific relevance. Ayunts, H., et al. [18] introduced SlantNet, a lightweight neural network tailored for thermal imagery. The model used a novel Slant Convolution (SC) layer to capture directional thermal gradients and thermal-specific augmentation strategies to address contrast and low-resolution challenges. SlantNet achieved about 95.1 % classification accuracy while reducing computational overhead by roughly 60%. Although architecturally efficient, the model lacked feature selection modules or grading stratagems that might elevate fine-grained defect discrimination. Batool, A., et al. [19] improved solar panel defect detection by enhancing the YOLOv8 framework, integrating Squeeze-and-Excitation Blocks (SEB) to amplify attention on critical defect regions like "Black Border" and "Broken" categories. This augmented architecture achieved improved detection focus and better performance on challenging defect types. Kavitha, R., et al. [20] presented a general AI-based framework for solar panel fault detection using machine learning methods. The system ingested imaging data and utilized standard classifiers to distinguish between fault classes.

3. PROPOSED SYSTEM

Ensuring the optimal performance of solar energy systems is crucial, as faults in PV modules can lead to significant energy losses and potential safety hazards. Traditional manual inspection methods are time-consuming and may not effectively detect underlying issues. Infrared thermography has emerged as a non-invasive diagnostic tool, capable of identifying anomalies such as hot spots and defective cells by visualizing temperature variations across PV panels. However, manual analysis of thermographic images is labour-intensive and subject to human error, necessitating the development of automated, accurate fault detection systems. Integrating machine learning techniques with thermographic imaging offers a promising approach to enhance fault detection in PV systems. By training algorithms on labelled datasets of thermographic images, these models can learn to recognize patterns associated with various faults, enabling rapid and precise classification.

3.2 Proposed System Architecture

Figure 2 shows the proposed system architecture. The process begins with an input thermal image, which undergoes preprocessing to enhance quality. The dataset is then split into training and testing sets before being passed through a VGG19-CNN model for feature extraction. A DNN classifier processes these features to classify the image into either a high or low state. Finally, performance analysis is conducted to evaluate the model's accuracy and effectiveness, ensuring reliable classification.

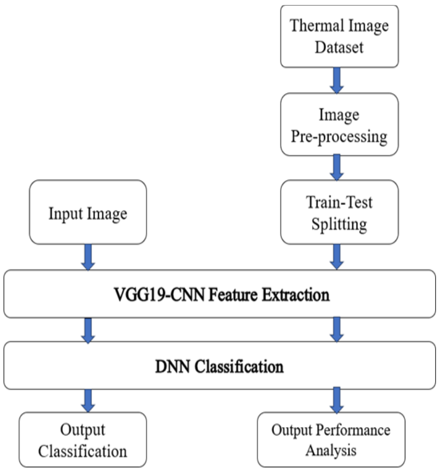

Figure 2: Proposed System Architecture.

3.3 Image Preprocessing

Image preprocessing techniques are essential for enhancing the accuracy of machine learning models in thermographic image classification for photovoltaic (PV) fault detection. Incorporating methods such as edge detection and Hough Transform can effectively identify structural anomalies like cracks or delamination in PV modules. These techniques highlight critical areas within thermographic images, enabling models to focus on regions indicative of faults, thereby improving diagnostic precision.

3.4 Thermal Image Analysis

Thermal image analysis offers significant benefits across scientific, industrial, and security domains due to its ability to detect and visualize heat signatures rather than relying solely on visible light. It enables non-contact temperature measurement, works effectively in low-light or no-light environments, and aids in identifying anomalies such as overheating components, energy loss, or hidden subjects. This capability is invaluable in predictive maintenance, medical diagnostics, surveillance, and environmental monitoring, as it provides real-time, precise, and actionable insights that are not possible with traditional imaging techniques.

3.5 Train-Test Splitting

Accurately detecting faults in PV systems using thermographic images requires a well-structured approach to training and evaluating machine learning models. One of the most important steps in this process is splitting the dataset into training and testing sets. The training set, usually comprising 70-80% of the data, is used to teach the model how to recognize patterns in thermal images, such as hot spots or other anomalies indicating faults. The remaining 20-30% of the data is reserved for testing, allowing us to assess how well the model performs on new, unseen images. A careful approach to splitting the dataset ensures reliable results.

3.6 Existing System Architecture

Ensuring optimal performance of solar energy systems is crucial, as faults in PV modules can lead to energy losses and safety hazards. Traditional manual

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inspections are time-consuming and may miss underlying issues as shown in Figure 2. Infrared thermography offers a non-invasive diagnostic method by visualizing temperature variations to identify anomalies like hot spots and defective cells. Integrating machine learning techniques with thermographic imaging enhances fault detection by training algorithms to recognize patterns associated with various faults, enabling rapid and precise classification.

Existing KNN (K-Nearest Neighbours): KNN is a classification model that predicts faults by finding similar data points. It compares new points with the closest samples in the training set. Labels are assigned based on the majority of nearest neighbours. This method is simple and effective for classification.

Existing RFC (Random Forest Classifier): RFC is an ensemble learning algorithm that builds multiple decision trees. It classifies data by averaging predictions from multiple trees. This reduces overfitting and improves accuracy. RFC is more robust compared to single decision trees.

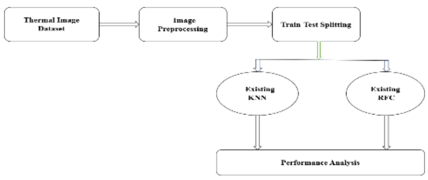

Figure 3: Existing System Architecture Block Diagram.

3.6.1 Existing KNN Classifier

The K-Nearest Neighbours (KNN) classifier as shown in Figure 4 is a simple and effective machine-learning algorithm used for classification tasks. It works by selecting an optimal value of K (number of neighbours) and calculating the distance between the test data and training samples. The algorithm finds the nearest neighbours based on this distance and assigns the test input to the majority class among the neighbours through majority voting. In the existing KNN classifier, preprocessing is done before splitting the dataset into training (X_Train, Y_Train) and testing (X_Test). The model is trained using selected features, and once trained, it predicts new data by comparing distances and choosing the most frequent class among its K neighbours. The trained model is then saved for future predictions, ensuring efficiency and accuracy in classification tasks.

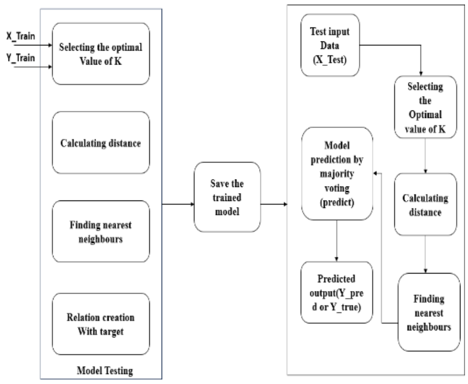

Figure 4: KNN Classifier Block Diagram

3.6.2 Existing RFC

The Random Forest Classifier (RFC) as shown in Figure 5 serves as the foundation of the ensemble learning process. It operates by splitting the dataset into multiple sub-training sets, with each subset used to train a different decision tree within the forest. By aggregating predictions from numerous individual trees, RFC produces a final classification that is both robust and precise.

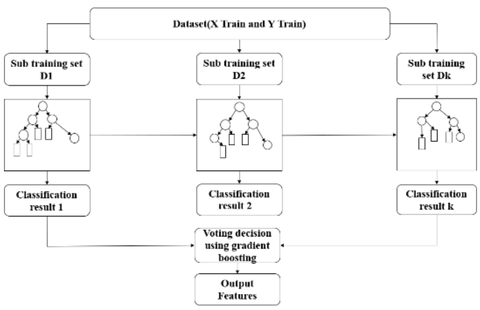

Figure 5: Existing RFC Block Diagram

3.7 Proposed VGG19 Feature Extraction

VGG19 module as shown in Figure 6 is a deep CNN architecture comprising 19 layers: 16 convolutional layers and 3 fully connected layers. It processes input images of size 224×224×3 (RGB) through five sequential blocks. Each block contains

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multiple convolutional layers with 3×3 filters, followed by ReLU activations, and concludes with a 2×2 max-pooling layer for down sampling.

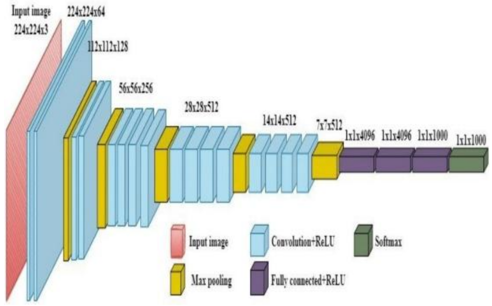

Figure 6: VGG19 Layer Block Diagram.

Convolution Layer: A convolutional layer in CNNs applies small, learnable filters (kernels) to scan an image and detect features like edges, textures, and patterns as shown in Figure 7 These filters generate feature maps that highlight important structures within the image. Early layers capture simple features, while deeper layers recognize complex shapes like objects or faces.

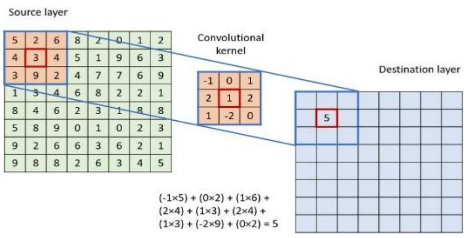

Figure 7: Convolution Layer

ReLU: This introduces non-linearity, helping neural networks learn complex patterns. It is defined as ReLU(x) = max (0, x). A major advantage of ReLU is preventing the vanishing gradient problem, improving training efficiency. It enables faster learning by allowing better gradient flow during backpropagation.

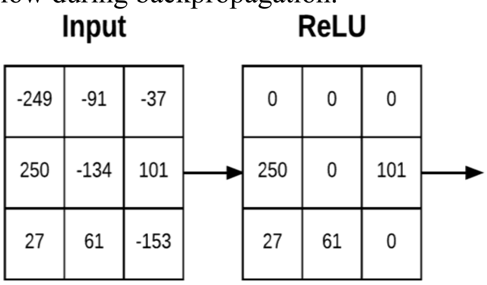

Figure 8: ReLU

Max Pooling: Max pooling as shown in Figure 9 is a down sampling technique in CNNs that reduces spatial dimensions. It divides the input into non- overlapping regions (e.g., 2x2 or 3x3) and selects the maximum value from each region. This reduces computational complexity, speeds up processing, and helps prevent overfitting

Average Pooling: Average pooling as shown in Figure 10 is a down sampling technique in CNNs that reduces spatial dimensions by computing the average of values within a fixed window, such as 2x2 or 3x3. Unlike max pooling, which selects the highest value, average pooling captures more generalized information by smoothing feature maps.

Fully Connected System: After the convolutional and pooling layers, the network moves to fully connected layers, where the 7×7×512 feature maps are flattened into a single vector of 25,088 elements.

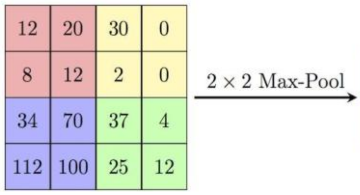

Figure 9: Max Pooling.

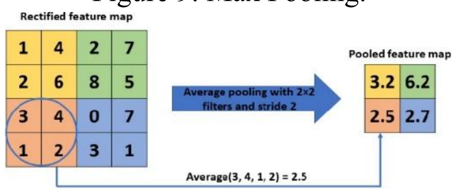

Figure 10: Average Pooling.

3.7.1 Proposed Dense Neural Network Classifier

This Dense Neural Network (DNN) classifier architecture offers several advantages, including its ability to capture complex nonlinear relationships between the VGG19-extracted features and the target output classes. The integration of multiple dense layers with Rectified Linear Unit (ReLU) activation functions enhances feature transformation and reduces the likelihood of vanishing gradients.

VGG19 Input Features: The network begins by receiving pre-extracted features from a VGG19 model, which acts as a deep feature extractor. These features represent high-level visual patterns such as textures, shapes, and edges, enabling the DNN classifier to focus on classification rather than raw pixel processing.

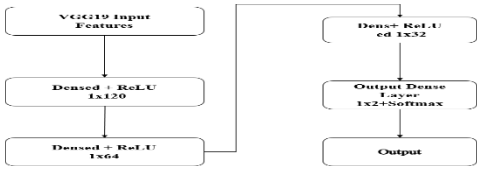

Figure 11: Dense Neural Network Classifier

4. RESULTS AND DISCUSSION

The dataset comprises 799 thermographic images organized into six folders, each representing specific conditions observed in photovoltaic (PV) systems: The Bird-Drop folder contains 198 images capturing instances where bird droppings have affected the surface of PV modules. Such droppings can cause localized shading, leading to hotspots and reduced energy output. Additionally, the acidic nature of bird droppings can corrode panel surfaces over time, potentially causing long-term damage if not addressed promptly. The Clean folder, comprising 193 images, serves as a control group, showcasing PV modules free from visible contaminants or defects. These images represent optimal operating conditions, providing a baseline for comparing and identifying anomalies in other categories.

Figure 12 shows machine learning-based thermographic image classification tool aimed at fault detection in photovoltaic arrays. It includes buttons for training, dataset upload, VGG19 feature extraction, dataset splitting, and classification using KNN, RFC, or a proposed VGG19-DNN model, along with options for test image prediction and exiting.

Figure 12: UI of Research Work

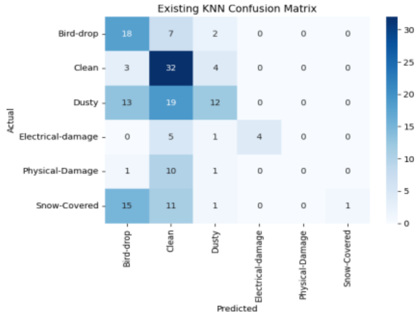

Figure 13: Confusion matrix of KNN

The confusion matrix presented in Figure 13 illustrates the classification results of a KNN model for different fault categories in photovoltaic panels. The diagonal cells show correct predictions, with "clean" panels having the highest accuracy (32 correct predictions). Misclassifications are visible, such as "dusty" panels being confused with "bird-drop" and "clean." The matrix highlights the challenges in distinguishing certain fault types and suggests the need for improved feature extraction or model tuning.

This confusion matrix presented in Figure 14 depicts the performance of a Random Forest Classifier in identifying faults in photovoltaic arrays. It reveals the number of correctly and incorrectly classified instances for each fault type. The matrix highlights areas where the model struggles, particularly in distinguishing between "Clean", "Dusty", and "Electrical-damage" categories, while accurately classifying "Snow-Covered" cases. Further model refinement is needed to improve overall accuracy and address misclassifications.

This confusion matrix presented in Figure 15 illustrates the exceptional performance of a Proposed VGG19 with DNN model for

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photovoltaic fault detection. It shows perfect classification for most categories, with all actual instances correctly predicted. A minor misclassification occurs where one "Dusty" case is predicted as "Physical-Damage".

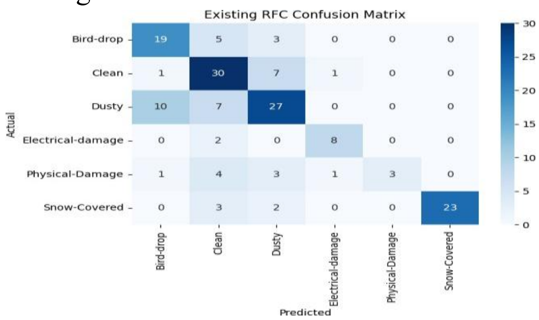

Figure 14: Confusion matrix of RFC.

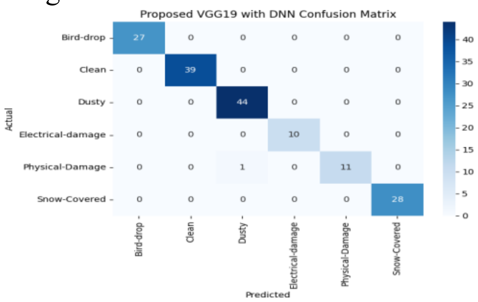

Figure 15: Proposed Confusion Matrix.

CONCLUSION

The performance comparison clearly highlights the significant improvement achieved by the proposed VGG19 with DNN model over the existing algorithms. The KNN classifier demonstrated relatively low performance with an accuracy of 41.8%, precision of 54.8%, recall of 41.8%, and an F1-score of 35.5%, indicating limited capability in handling the complexity of the classification task. The RFC algorithm showed better performance, achieving an accuracy of 68.7%, precision of 72.3%, recall of 68.7%, and an F1-score of 68.3%, but still left room for improvement in both accuracy and predictive reliability. In contrast, the proposed VGG19 with DNN model achieved perfect classification results with 100% accuracy, precision, recall, and F1-score. This demonstrates its ability to accurately and consistently classify Solar PV system data without misclassification, reflecting superior feature extraction and decision-making capabilities. Such outstanding results indicate that the proposed model is highly efficient, robust, and well-suited for real-world applications, offering a significant advancement over conventional approaches.

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