A Hybrid CNN-SVM Model for High-Accuracy Defect Detection in PV Modules Using Infrared Images

Rachid Zaghdoudi, Nadir Fargani*

[1] Research Center in Industrial Technologies CRTI, P.O.Box 64, Cheraga, Algeria
*Corresponding author; Email: nadirfergani@yahoo.fr

Article Info

Article history:

Received , 02/03/2024
Revised , 15/04/2024
Accepted , 12/05/2024

Keywords:

Solar energy
Defect detection
CNN
SVM
Thermography
PV modules

ABSTRACT

This paper presents a novel approach for classifying infrared solar modules using a hybrid CNN-SVM model. The proposed method involves several key steps: preprocessing using histogram equalization to enhance image contrast, data augmentation to increase the diversity of the training set, feature extraction using a Convolutional Neural Network (CNN), and final classification with a Support Vector Machine (SVM) classifier. To evaluate the effectiveness of this approach, we used a comprehensive infrared solar modules dataset comprising 20,000 images. The hybrid model achieved an overall accuracy of 92.67%, with a precision of 90.85%, recall of 93.10%, and F1 score of 92.46%, demonstrating significant improvements over existing state-of-the-art methods. Comparative analysis with recent studies further validates the effectiveness of our approach. This work underscores the potential of combining deep learning with traditional machine learning techniques for enhanced solar module inspection and quality assurance.

I. Introduction

Solar energy is increasingly recognized as a crucial renewable resource due to its role in providing clean and sustainable energy. It does not produce harmful gases or environmental pollutants, helping to reduce carbon emissions and mitigate global warming. As an inexhaustible source, solar energy supports long-term energy sustainability. The installation of solar panels reduces electricity costs for individuals and businesses, with relatively low operational and maintenance costs after the initial investment. This not only improves energy independence but also strengthens national energy security and boosts economic growth by creating jobs in manufacturing, installation, and maintenance.

The versatility of solar energy extends to various applications, including electricity production for homes and businesses, powering devices, heating water, and supporting agricultural processes such as water desalination and irrigation. Its adaptability allows it to be installed in diverse locations, thus reducing the need for extensive infrastructure and promoting local energy self-sufficiency.However, as photovoltaic (PV) plants grow in size, manual inspection of defects becomes impractical and economically inefficient. Therefore, it is crucial to implement automated systems for defect detection, diagnosis, and isolation. Recent advancements in imaging technologies, particularly infrared thermography, have proven beneficial in this regard. Infrared thermography provides a non-destructive means of detecting thermal anomalies such as hot spots, cracks, and degradation without interrupting system operation. It offers real-time thermal images that facilitate the rapid analysis of large installations, enabling early identification of potential defects and supporting proactive maintenance.Recently, advancements in deep learning have revolutionized the field of imaging inspection. Convolutional neural networks (CNNs) have demonstrated exceptional performance in extracting relevant features from complex images. By combining these machine learning techniques with infrared imaging methods, it is now possible to significantly improve the accuracy and efficiency of defect detection. Deep learning models enable finer analysis and more precise classification of anomalies, overcoming the limitations of traditional methods.

Several recent studies have explored various methods for classifying defects in photovoltaic modules using thermal images. For instance, Akram et al. [1] developed a framework for automatic defect detection in photovoltaic modules using infrared images, achieving an accuracy of 98.67% with a standalone deep learning model and 99.23% with a transfer learning model.To assess real-time inspection capabilities, the authors in [2] implemented the CNN model on an edge device, achieving an accuracy of 85.4% for classifying the 12 classes. This implementation demonstrates the practical viability of using CNNs for real-time defect detection in a constrained environment. Bu et al. [3] introduced a CNN model with a residual architecture for classifying defects in PV cells using infrared thermography, achieving an accuracy of 96.96% across three defect classes. Haidari et al. employed an enhanced VGG16 architecture with an improved fully connected layer for transfer learning in classifying defects in photovoltaic modules, achieving 98% accuracy [4]. Gopalakrishnan et al. [5] proposed a NASNet-LSTM classifier for detecting anomalies in photovoltaic modules. Their approach combines the NASNet convolutional neural network with long short-term memory (LSTM) networks to classify electrical and non-electrical anomalies in PV modules, achieving 84.75% accuracy. R. Aman et al. [6] examined the impact of dust on PV modules using a thermal imager to detect hot spots and classify defects, with AlexNet achieving 99.3% accuracy. Alves et al. [7] developed a method using CNNs for automatic classification of defects in PV modules, with data augmentation techniques improving CNN performance to achieve 92.5% accuracy in anomaly detection. Nagar and Rai [8] used ResNet-9 architecture with filter pruning to detect anomalies in solar panels using infrared images, achieving an accuracy of 80.2% on a set of 20,000 labeled images. Recently, Ramadan et al. [9] proposed an advanced Vision Transformer (ViT) model for automatic defect detection in infrared images of PV modules, achieving 98.23% accuracy for binary anomaly classification and 95.55% for classifying twelve defect types, including no anomaly.

The primary objective of this study is to develop an automated classification system for infrared images of solar modules by integrating convolutional neural networks (CNNs) with a support vector machine (SVM) classifier. Specifically, the study aims to design a CNN model capable of extracting relevant features from infrared images and classifying them into 12 distinct defect categories. These feature vectors, extracted by the CNN model, will subsequently be fed into a support vector machine (SVM) to assess its effectiveness in defect classification.

II. Description of the Infrared Solar Modules Dataset

The infrared solar modules dataset [10] used in this study consist of 20,000 images of PV modules, classified into twelve categories. These images, captured by Raptor Maps Inc. using medium-wave and long-wave infrared cameras (3–13.5 µm) from manned aircraft and UAV systems, have a resolution of 24 × 40 pixels and an 8-bit depth. Spatial resolution ranges from 3.0 to 15.0 cm/pixel. The dataset includes 10,000 images of PV modules with no anomalies and the remaining 10,000 images are distributed across eleven different anomaly classes, such as diodes, multi-diode, hot spot, and shading. This dataset provides a diverse range of defects, enhancing the generalization of defect detection models. Figure 1 displays samples of typical defects found in the infrared solar module defects database.

III. Methodology

This section describes the methodology employed for defect detection and classification in infrared images of photovoltaic (PV) modules. The process is divided into several steps: data preprocessing, model architecture, training, and evaluation.The block diagram of the proposed methodology is illustrated in Figure 2, with the steps involved in the system described below.

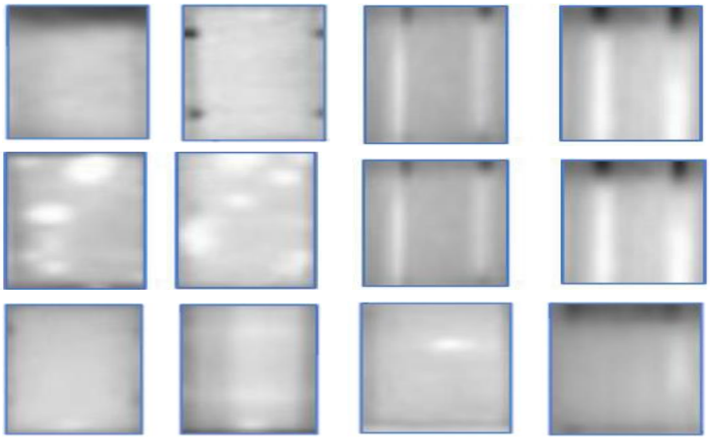

Figure 1. Representative Samples of Typical Defects in the Infrared Solar Module Defects Dataset.

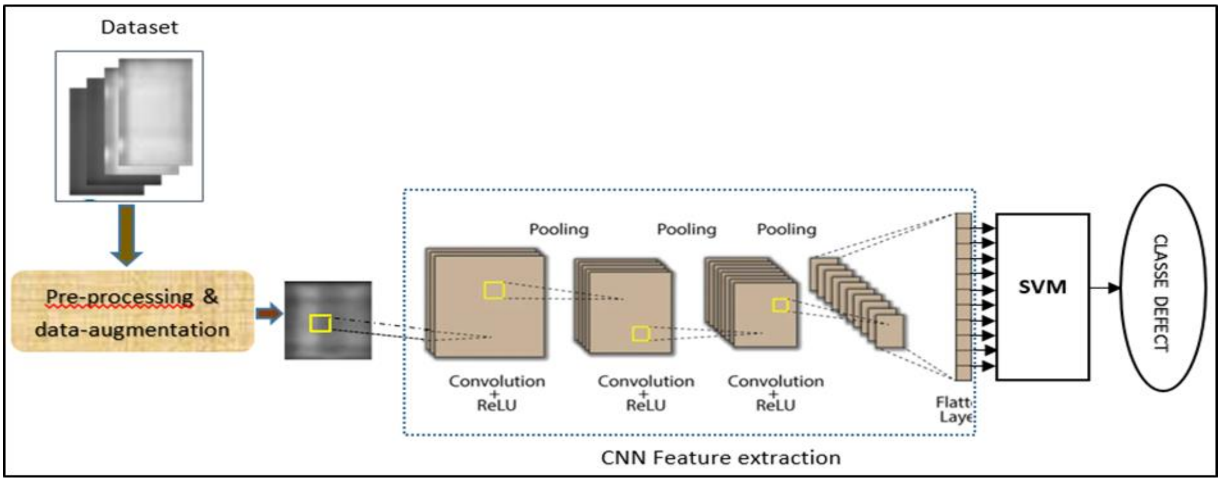

Figure 2. Block Diagram of the Proposed Methodology and System Workflow.

III.1. Data Preprocessing

1) **Normalization**: Each image is normalized to ensure pixel values are in the range [0, 1] to facilitate better convergence during training.
2) **Adaptive Histogram Equalization**: To enhance image contrast and highlight defect regions, adaptive histogram equalization (AHE) is applied. This technique adjusts the contrast of each image by redistributing pixel intensity values, helping to emphasize important features.
3) **Data Augmentation:** To address class imbalance and improve model robustness, various augmentation techniques are applied. This process includes rotations, horizontal and vertical flips, and brightness adjustments. Specifically, each image is augmented with 180-degree rotations, horizontal and vertical flips, and brightness adjustments ranging from ±30%. These operations generate diverse variations while preserving the true nature of the anomalies. Augmentation is performed such that the underrepresented defect classes are significantly increased, while the 'No Anomaly' class is selectively augmented. This approach ensures a balanced representation of all classes in the training and validation sets.

4) **Splitting:** The dataset is divided into training, validation, and test sets. Specifically, 70% of the data is used for training, 15% for validation, and 15% for testing.

III.2. Model Description

The model employs a Convolutional Neural Network (CNN) to extract features from infrared images of photovoltaic modules, which are then used by an SVM classifier. The CNN architecture includes:

1) **Convolutional Layers**
Comprising several Conv2D layers with increasing filters (32, 64, 128, 256, and 512) and ReLU activation, these layers detect increasingly complex features from the images, ranging from simple edges to detailed patterns.
2) **Batch Normalization**
Applied after each convolutional layer to stabilize and accelerate training.
3) Max Pooling
Reduces the spatial dimensions of feature maps while preserving important information.
4) Fully Connected Layers
After flattening the features, dense layers with ReLU activation and dropout (0.5) regularization are used to extract high-level features.
5) **Output Layer**
A dense layer with softmax activation produces the final feature vectors for the 12 classes.

This CNN model extracts discriminative features from the images, facilitating precise classification by the SVM.

III.3. Implementation Details

In this experiment, the dataset was partitioned into training, validation, and testing sets with proportions of 70%, 15%, and 15%, respectively. The model was trained for 20 epochs using a batch size of 32 images. The Adam optimizer was employed for model optimization with a learning rate of 0.0001. All experiments were conducted using TensorFlow 3.12.10 on the Google Colaboratory platform with a Tesla T4 GPU.

IV. Results and Discussion

In this section, we present the performance evaluation of the proposed hybrid CNN-SVM model for defect detection in photovoltaic (PV) modules using infrared images. To enhance the credibility of the experimental results, four key evaluation metrics were used: accuracy, recall, precision, and F1-score. These metrics are defined as follows:
Accuracy measures the proportion of correct predictions (both true positives and true negatives) among all predictions. It is calculated using:

$$\frac{TP+TN}{TP+FP+TN+FN} \qquad (1)$$

Recall (or Sensitivity) quantifies the proportion of actual positive cases that were correctly identified. It is given by:

$$\frac{TP}{TP+FN} \qquad (2)$$

P**recision** measures the proportion of predicted positive cases that are actually positive. It is calculated as:

$$\frac{TP}{TP+FP} \qquad (3)$$

F1-Score is the harmonic mean of precision and recall, providing a balance between the two metrics. It is computed using:

$$2\ x \frac{Precision\ x\ Recall}{Precision\ +Recall} \qquad (4)$$

Here, TP represents True Positives, TN denotes True Negatives, FP stands for False Positives, and FN signifies False Negatives.

Table 1Performance Metrics of the CNN Model on Infrared Solar Module Classification

Class	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
No-Anomaly		83.77	73.52	78.31
Cell		90.57	86.35	88.41
Vegetation		98.91	94.90	96.86
Diode		93.01	97.96	95.42
Cell-Multi		99.22	100	99.60
Shadowing		99.84	81.97	90.03
Cracking		99.08	98.94	98.77
Offline-Module		66.79	85.94	75.17
Hot-Spot		90.20	96.21	93.11
Hot-Spot-Multi		95.65	87.05	91.15
Soiling		99.71	94.46	97.02
Diode-Multi		80.24	91.43	85.47
Overall	90.71	88.56	82.99	85.48

Table 1 summarizes the classification results achieved using the proposed CNN model on the test set in terms of loss, accuracy, precision, recall, and F1 score. As shown, the proposed CNN model demonstrates strong overall performance with an accuracy of 90.71%. However, specific areas require improvement: the No-Anomaly and Offline-Module categories exhibit lower precision and recall, indicating a need for model enhancement to reduce false positives and increase true positive detections. In contrast, categories like Cell-Multi, Cracking, and Soiling show near-perfect performance, suggesting the model is highly effective in these areas. The next phase involves using this CNN model as a feature extractor for an SVM classifier, which might further improve classification performance by leveraging the strengths of both models. Additionally, Figure 3 shows the confusion matrix, providing a visual representation of the model's performance across all classes.

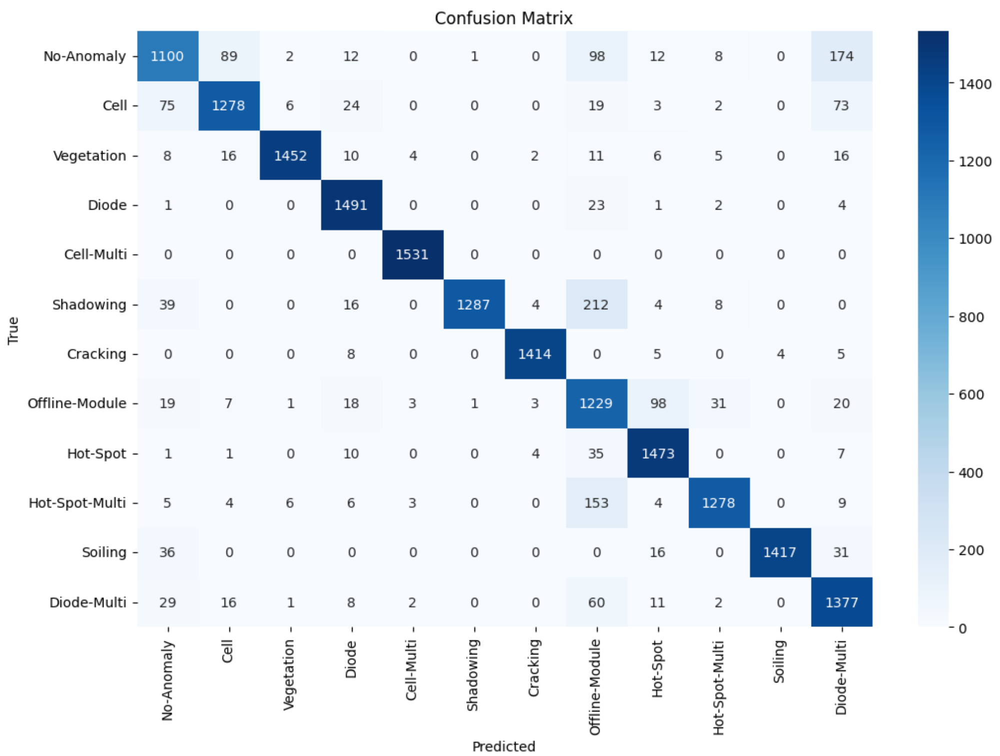

Figure 3. Confusion matrice of the proposed CNN model.

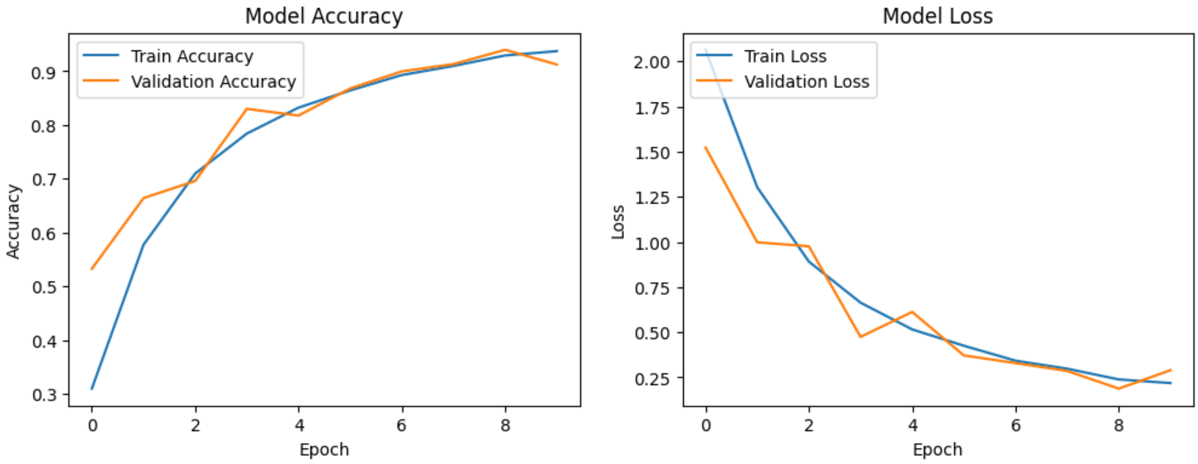

Figure 4. Accuracy and loss of the proposed CNN model.

Figure 4 shows graphic representations of the training and validation accuracies and losses among the model under evaluation, providing insight into the learning dynamics and generalization capability of the model.

We now present the results obtained with the hybrid CNN-SVM system for the classification of infrared solar modules. This system combines the feature extraction capabilities of the CNN model with the classification power of the SVM, providing an integrated approach to enhance the accuracy and robustness of the classification.Table 2 summarizes the classification results obtained using the proposed hybrid CNN-SVM model on the test set, covering metrics such as loss, accuracy, precision, recall, and F1 score.

Table 2. Performance Metrics of the CNN-SVM Hybrid Model for Infrared Solar Module Classification

Class	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**
No-Anomaly		78.34	87.77	82.79
Cell		90.27	85.88	88.02
Vegetation		99.38	94.44	96.85
Diode		99.19	96.39	97.77
Cell-Multi		99.48	100.00	99.74
Shadowing		97.93	99.55	98.74
Cracking		99.51	99.44	99.48
Offline-Module		74.60	88.11	80.80
Hot-Spot		89.96	96.54	93.13
Hot-Spot-Multi		95.45	87.26	91.17
Soiling		97.47	100.00	98.72
Diode-Multi		95.67	76.23	84.85
Overall	92.69	90.85	93.10	92.46

From the Table 2, the hybrid CNN-SVM system demonstrates an impressive overall accuracy of 92.69%, reflecting a significant improvement over the standalone CNN model. Detailed metrics for each class reveal the following performance:
The hybrid CNN-SVM system achieves an impressive accuracy of 92.69%, demonstrating notable improvements over the standalone CNN model. Key performance metrics include:

- No-Anomaly: Enhanced recall with 87.77%, improving detection of non-anomalous instances.
- Cell: Balanced precision (90.27%) and recall (85.88%), maintaining high performance.
- Vegetation: Very high precision (99.38%) and recall (94.44%), reflecting excellent identification.
- Diode: High precision (99.19%) and recall (96.39%), showing strong classification.
- Cell-Multi: Near-perfect performance with precision (99.48%) and 100% recall.
- Shadowing: Improved recall (99.55%) and precision (97.93%).
- Cracking: High precision (99.51%) and recall (99.44%).
- Offline-Module: Higher recall (88.11%) but lower precision (74.60%).
- Hot-Spot: Enhanced recall (96.54%) and good precision (89.96%).

- Hot-Spot-Multi: High precision (95.45%) and moderate recall (87.26%).
- Soiling: Perfect recall (100%) and high precision (97.47%).
- Diode-Multi: Improved precision (95.67%) with lower recall (76.23%).

Overall, the hybrid CNN-SVM system significantly enhances classification performance, demonstrating improved precision and recall across most categories. This combined approach leverages the strengths of both models, resulting in a more accurate and reliable system for classifying infrared solar modules.. Additionally, Figure 5 presents the confusion matrix, offering a visual representation of the hybrid CNN-SVM model's performance across all classes.

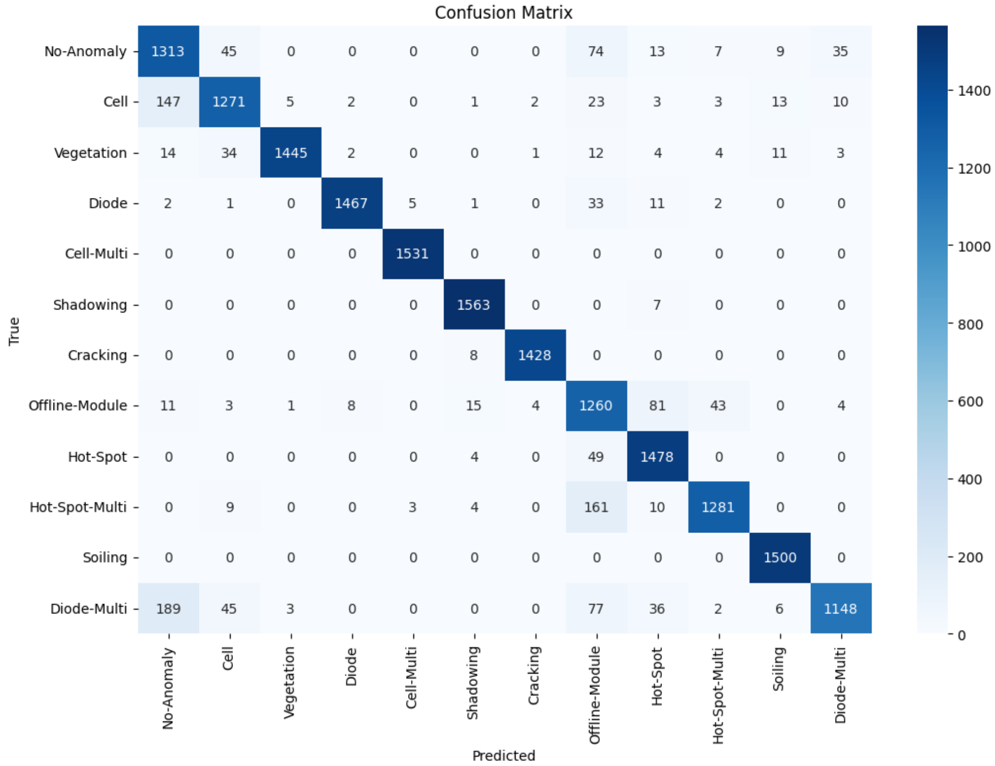

Figure 5. Confusion matrice of the proposed hbrid CNN-SVM model.

To further demonstrate the effectiveness of the proposed model, its accuracy is compared against various state-of-the-art results reported in recent studies using the same infrared solar module dataset.

Table 3: Performance Comparison of the Proposed Hybrid CNN-SVM Model with Existing Systems

System	Accuracy (%)	Precision (%)	Recall (%)	F-Score (%)
Le M [2]	85.90	-	-	-
Nagar and Rai [8]	80.20	-	-	-
Duranay [11]	93.93	91.50	88.29	89.82
Minhhuy Le [12]	86.00	-	-	-
Proposed system	92.67	90.85	93.10	92.46

Table 3 presents a comparative performance analysis of the proposed hybrid CNN-SVM model against several existing systems. The proposed model achieves an impressive accuracy of 92.67%, with a precision of 90.85%, recall of 93.10%, and F1 score of 92.46%. This represents a significant improvement over previous systems. For instance, Duranay's model, which had the highest reported accuracy among the compared systems, achieved 93.93% accuracy but with lower precision and recall. Other systems, such as those by Le M, Nagar and Rai, and Minhhuy Le, showed lower performance metrics across the board. The proposed CNN-SVM system thus demonstrates superior overall performance in the classification of infrared solar modules.

V. Conclusion

In this paper, we presented a hybrid CNN-SVM model for the classification of infrared solar modules, demonstrating its efficacy in enhancing the accuracy and robustness of defect detection. Through extensive experimentation and analysis, the hybrid model achieved an impressive overall accuracy of 92.67%, significantly outperforming several state-of-the-art approaches. Detailed class-wise metrics highlighted the model's strengths, particularly in accurately identifying complex defect categories, while addressing the limitations observed in standalone CNN models.

The CNN component effectively captured intricate features from the infrared images, which were then leveraged by the SVM classifier to improve decision boundaries and enhance classification performance. The comparative analysis with existing systems underscored the advantages of our hybrid approach, offering superior precision, recall, and F1 scores.

Future work will focus on further optimizing the hybrid model by exploring different CNN architectures and kernel functions for the SVM classifier. Additionally, we plan to investigate the application of this approach to other types of solar modules and expand the dataset to include more diverse defect scenarios. The promising results obtained from this study provide a strong foundation for the development of more reliable and accurate defect detection systems in the field of solar energy.

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