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Enhanced Fault Identification in Solar Panels through Binary Cascaded Convolutional Classifiers with Thermal-Visual Image Augmentation

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Abstract: Solar power stands as a pivotal renewable energy source for the twenty-first century. However, the optimal functioning of solar panels is often hindered by various faults, necessitating accurate and early defect detection to maximize energy production. Existing solar panel fault identification models encounter challenges such as low precision, difficulty in distinguishing fault types, and poor generalization due to limited and unbalanced data samples. This paper introduces a novel and effective approach, leveraging a Binary Cascaded Convolutional Classifier augmented with visual and thermal image combinations to address these limitations. The proposed model adeptly classifies five distinct types of solar panel faults, including single cell hotspots, diode hotspots, dust/ shadow hotspots, multicell hotspots, and Potential-Induced Degradation (PID) hotspots. Through image augmentation techniques like rotation, shifting, sheering, resizing, jittering, and blurring applied to visual and thermal images, inter-class feature variance is increased. Binary Cascaded Convolutional Neural Network (BCCNN) classifiers are trained using an enriched dataset, each specifically designed to differentiate between dust/ shadow hotspots and other fault categories. The adoption of a binary method significantly enhances precision, allowing for focused fault identification and classification. The proposed model surpasses existing literature in terms of precision (99.8%), accuracy (98.5%) and recall (98.4%), underscoring its effectiveness across all five fault classes. In summary, this research marks a substantial advancement in the realm of solar panel fault identification, presenting a more precise and effective fault detection methodology that has the potential to significantly enhance the maintenance and longevity of solar energy systems.

Index Terms: Binary Cascaded Convolutional Neural Network; CNN; Image Augmentation; Solar Energy; Solar Panel Fault Detection

1. Introduction

Solar energy has become a well-known source of renewable energy in the contemporary period of growing environmental awareness and energy demand levels. It provides a clean, plentiful, practically limitless power source. Being at the centre of this energy conversion process, solar panels play an important role in the effective use of solar electricity process. The performance and dependable operation of solar panels are, nevertheless, frequently hampered by several issues that occurred in different cases. If left unidentified and unaddressed across various scenarios, these issues can substantially reduce the efficiency and lifespan of solar panels [1,2,3].

Single cell hotspots, diode faults, dust and shadow hotspots, multicell hotspots, and Potential Induced Degradation (PID) effects are among the common problems in solar panels. Most of the fault detection approaches now in use rely on slow, error-prone manual examination and outdated image processing technologies. Additionally, these traditional methods frequently produce inadequate fault diagnosis because of their inability to distinguish between various issue types [4,5,6]. Additionally, due to small and unbalanced data sets, present machine learning models for problem identification frequently suffer from insufficient generalization. The inability of these models to maximize the inter-class feature variance, which hinders the identification of various types of errors, reduces the precision of these models.

To overcome these difficulties, this research suggests a unique method for solar panel fault detection by creating a powerful Binary Cascaded Convolutional Neural Network (BCCNN) Classifier with augmentation. With a large collection of enhanced photos that simulate various solar panel problems, this model is intended to solve the drawbacks of earlier ones. To distinguish between dust and shadow hotspots and the other four fault categories, our BCCNN classifiers have been specially trained. It is a highly concentrated and targeted fault detection technique by utilizing binary classifiers. A solar panel thermal image is automatically classed as a dust and shadow hotspot if it does not fit into any of the categories set out by the binary classifiers. This auto classification of a thermal image ensures that no errors are missed. The BCCNN model demonstrates outstanding performance across all categories concerning precision, accuracy, recall, and Area Under the Curve (AUC). This showcases its effectiveness in early and accurate identification of diverse solar panel issues. This advancement holds promising potential to considerably enhance the maintenance and longevity of solar energy installations.

This paper is organized as: Review of the existing models used for fault detection is discussed in section 2. The proposed model is thoroughly described in section 3. A thorough analysis of the design and outcomes of the experiment are discussed in section 4. At the end summary with major discoveries and potential future scopes in covered.

2. Review of Existing Models Used for Fault Analysis

As the utilization of solar energy has surged in recent years as a prominent renewable energy source, the research focus on fault identification in solar panels has intensified. Studies have examined both conventional methods of fault identification and more recent machine learning techniques [7,8,9]. In the beginning, problem detection methods were mainly manual and heavily reliant on visual inspections, thermal imaging, and the use of infrared (IR) cameras. For instance, work in [10,11,12] used infrared thermography to find irregularities in photovoltaic (PV) panels. Although straightforward, these techniques have some drawbacks such the requirement for specialized knowledge, their time-consuming nature, and their incapacity to identify problems in their early phases.

Machine learning-based techniques have drawn interest recently due to their capacity to automate defect identification. However, each of these approaches has a unique set of difficulties. Most of these models lack generalizability in defect identification since they were trained on small, unbalanced datasets and samples. The capacity of many existing models to distinguish between distinct fault types is further constrained by their difficulty in optimizing inter-class feature variance levels [13,14,15].

Convolutional neural networks (CNN) have significantly advanced the field of fault detection. CNN-based models have proven to be more effective than conventional image processing models because they can automatically learn and extract complex characteristics from images. According to [16,17,18], these models frequently struggle with the binary classification of flaws. These models often categorize an image as having a fault but cannot recognize the precise sort of fault.

Few studies have also tried to enhance the data used to train machine learning models by using picture augmentation techniques. Data augmentation techniques were used in the work [19, 20] to improve the training dataset for fault identification process. Despite the advancements, the models still had trouble differentiating between different fault kinds via use of MobileNetV2 and Linear Discriminant Algorithms (MVN LDA) [21, 22, 23].

In summary, the current methods for fault detection in solar panels have demonstrated promising results. But there are still several significant limitations which are as follows:

- A lack of generalization caused by insufficient and unbalanced data.
- An inability to maximize inter-class feature variance.
- Challenges in accurate binary classification process [24,25,26].

These difficulties highlight the need for more complex models that can better identify faults in solar panels. More exactly models like UNet [27, 28], Principal Component Analysis (PCA) [29, 30] have also paved the way for better classification but have higher complexity when applied to real-time scenarios. To overcome these issues, the next section proposes the design of an efficient Binary Cascaded Convolutional Neural Network (BCCNN) model, which assists in enhancing efficiency while reducing complexity under real-time scenarios.

3. Proposed Design of BCCNN for Fault Identification in Solar Panels

Reviewing existing fault identification models for solar panels reveals their complexity or reduced efficiency when handling real-time fault images. Thermal image dataset for solar panels often suffers from class imbalance, where some faults are rare such as dust/shadow hotspot. Multiclass classifiers tend to bias toward majority classes. In contrast, Binary classification enables focused training on two classes at a time (e.g., Fault-1 vs Fault-2). Each binary CNN can be individually optimized for separating two specific fault types, improving performance on minority classes. Multiclass classifiers must learn complex decision boundaries in high-dimensional space. Binary classifiers only need to separate two classes, leading to lower model complexity per classifier and improved generalization, particularly when classes are visually similar (e.g., single cell and multicell hotspot). Cascaded binary CNNs are modular. New faults can be added by training new binary classifiers without retraining the entire system. Fault combinations can be managed more efficiently through hierarchical or pairwise structures.

Addressing these concerns, this section outlines the design of an effective Binary Cascaded Convolutional Neural Network (BCCNN) classifier for precise solar panel fault identification. As per Figure 1, the proposed model initially augments collected thermal and visual images of solar panel. These augmented images are classified into N different fault classes via use of BCCNN model. Binary classification has better efficiency than multiclass classification for the same image sets. Due to use of BCCNN, complexity of classification is reduced while the precision & accuracy levels are also enhanced. All input images are augmented using rotating, shifting, sheering, resizing, jittering, and blurring operations.

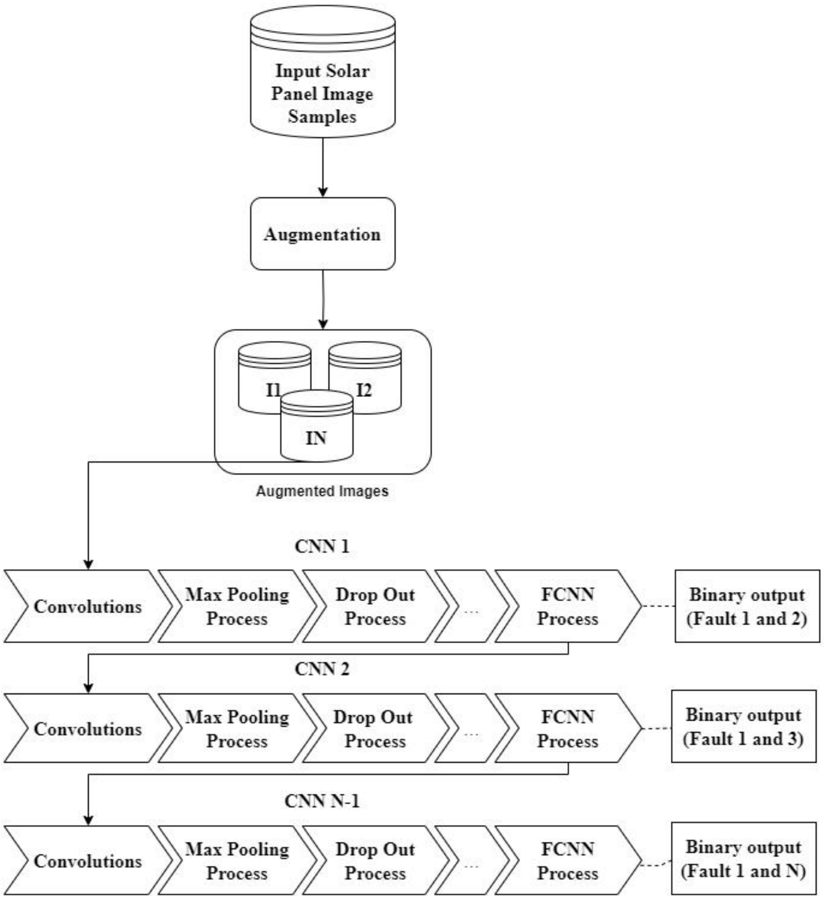

Fig. 1. Flow of the proposed BCCNN Model for identification of solar panel faults

Once the images are augmented, then they are passed through an efficient BCCNN classifier, which assists in identification of different solar panel faults. The Binary Cascaded Convolutional Neural Network (BCCNN) model implemented leverages a structured and moderately tuned set of hyperparameters to balance performance with training efficiency. The key hyperparameters configured include an input image size of 150×150×3, which standardizes input dimensions for both thermal and RGB images, and a batch size of 16 for training, which strikes a balance between computational efficiency and gradient stability. The model is trained for 10 epochs, with each epoch comprising 10 steps per epoch and 10 validation steps, ensuring consistent evaluation during training. The optimization strategy utilizes the Stochastic Gradient Descent (SGD) optimizer. The loss function is categorical cross entropy, suitable for binary classification when labels are one-hot encoded, and SoftMax activation is used in the output layer to produce class probabilities. Mathematically the model can be represented as,

Given an image $x \in R^{150\times150\times3}$

$$f_{conv}(x) = BCCNN(x)$$

Let:
$f \in R^k$ be the flattened feature vector.
The final dense layer applies softmax as:

$$\hat{y} = softmax\,(W.f + b)$$

$$\hat{y}_i = \frac{e^{W_i f + b_i}}{\sum_{j=1}^{2} e^{W_i f + b_j}}$$

Loss can be expressed as:

$$\mathcal{L} = -\sum_{i=1}^{2} y_i \log\,(\hat{y}_i)$$

Figure 2 illustrates the classifier design, showcasing a cascaded arrangement of convolutional, max pooling, and dropout layers. This configuration aims to identify high-density feature sets for fault identification. These feature sets are extracted via equation 1, where augmented images are fused with Rectilinear Unit (ReLU) activations as follows,

$$Conv(out) = \sum_{a=-\frac{m}{2}}^{\frac{m}{2}} \sum_{b=-\frac{n}{2}}^{\frac{n}{2}} AI(i-a, j-b) * ReLU\left(\frac{m}{2} + a, \frac{n}{2} + b\right) \quad (1)$$

where, m, n are different sizes for windows which can be observed from Figure 2, while AI is the augmented image, and a, b are stride sizes.

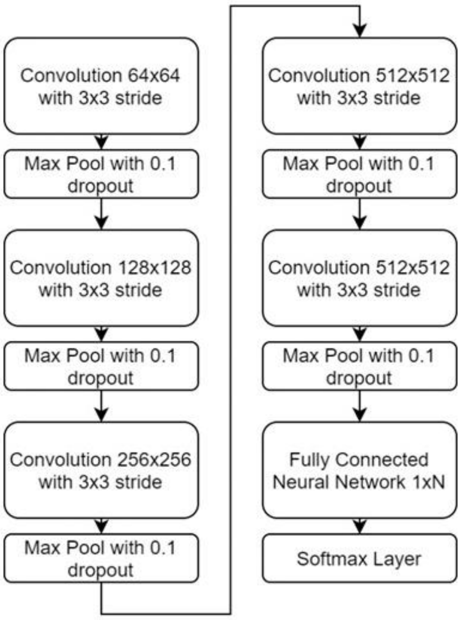

Fig. 2. Layered Diagram for the BCCNN Process

These features are passed through Max Pooling operations, which estimates an iterative feature threshold via equation 2,

$$f_{th} = \left(\frac{1}{X} * \sum_{x \in X} x^p\right)^{\frac{1}{p}} \quad (2)$$

where f_{th} = feature threshold, f = feature extracted, p = pooling window size, x = input

All features with $f > fth$ are passed to the next set of iterations, while others are discarded from the classification process. After repeating this process for all layers, the final features are passed through an efficient Fully Connected Neural Network (FCNN), which converts the extracted features into binary classes via equation 3,

$$C(out) = SoftMax\left(\sum_{i=1}^{Nf} f(i) * w(i) + b(i)\right) \quad (3)$$

where, N_f are the total feature counts, and w, b are the respective weights & biases for individual features. The output class $C(out)$ is evaluated via SoftMax activation, which is responsible for tuning the weights & biases. For N faults, this model deploys N-1 classifiers, which are converged via equation 4,

$$C(final) = CC,\ if\ converge \\ else,\ \vee_{i=1}^{NF} VC(out, i) \tag{4}$$

where, NF are the total number of faults, CC represents the class common to all classifiers, while VC represents the output class by individual classifiers. Using these operations, the proposed model can identify different fault types with higher efficiency levels. Evaluation of these efficiency levels is discussed in the next section, where these levels are compared between existing models for different fault types.

4. Statistical Analysis and Comparison

In this study, the performance of the BCCNN is rigorously evaluated for detecting solar panel faults using a comprehensive experimental setup. The study aimed to assess the model's accuracy in identifying and categorizing various solar panel faults. To achieve this, a diverse dataset is created comprising color and thermal images by depicting various solar panel faults. These solar panel faults include single cell hotspots, diode hotspots, dust/shadow hotspots, multicell hotspots, and PID hotspots. Augmentation techniques are applied to each image for enlarging the dataset and improving the model's ability to generalize. This diversity enabled the model to learn from various scenarios. To examine the dataset's influence on performance and generalization, sample sizes varied from 250 to 10k in increments of 500. Figure 3 illustrates some sample images.

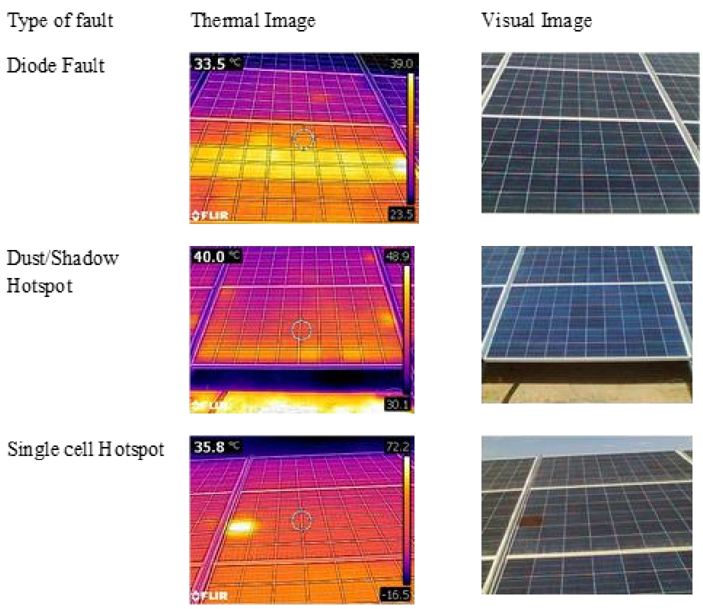

Fig. 3. Sample thermal and visual images

The performance of the proposed model has been compared with the current models using accuracy, precision, recall and F1 score. Each model's computational efficiency is calculated and studied to identify a problem (delay) in terms of milliseconds. In the experimental process, a ratio of 20:60:20 is used to partition the dataset into validation, training, and testing sets. The training dataset has been used to train the models, and the hyperparameters are tuned for the best results. For each dataset size, the training and evaluation steps are repeated numerous times to ensure statistical significance levels. Precision (P), Recall (R), Accuracy (A), Delay (D), and F1 score values were used to measure this performance. Accuracy is determined by using equation 5. Accuracy is a measure of how many solar panel entities that were reviewed are correctly identified out of all the solar panel images. The equation for accuracy is as follows,

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

where:

TP represents the count of correctly detected positive solar panel images.

TN denotes the number of accurately identified negative solar panel images.

FP stands for the count of falsely identified positive solar panel images.

FN indicates the quantity of incorrectly missed negative solar panel images.

Precision is computed using equation 6. It signifies the percentage of accurately detected positive solar panel images among all the solar panel images identified as positive.

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

Recall quantifies the ratio of correctly identified positive solar panel images among all the positive and false negative solar panel images within the datasets and samples. It is determined using equation 7,

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

Likewise, the F1 score represents a harmonic means of precision and recall, providing an assessment of the method's overall performance. This is computed using equation 8.

$$\text{F1}\ score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{8}$$

Delay represents the time consumed for extracting and measuring solar panel entities using specific methods. It stands as a crucial factor in assessing the feasibility and practicality of a solar panel entity extraction method. Delay is calculated using equation 9.

$$D = ts(complete) - ts(start) \tag{9}$$

where, ts represents the timestamp for completion and starting the classification operations.

BCCNN was made up of several binary CNN classifiers, each of which was designed to separate out distinct types of faults from single cell hotspots. The dataset is applied to various existing deep learning architectures by transfer learning with hyperparameter tuning. F1 score for each model is calculated. The comparison of proposed model with existing architectures can be observed from Table 1.

Table 1. Comparison of classification results using deep learning

Deep Learning Model	F1 Score
ResNet-50	0.85
VGG-16	0.65
VGG-19	0.66
Xception	0.81
DenseNet-121	0.67
DenseNet-169	0.71
BCCNN (Proposed model)	0.99

Along with transfer learning, the same dataset is applied by taking the concepts of architecture from three models MVN LDA, UNet, and PCA-CNN. These models are developed and modified by taking the concept to handle the process of identifying solar panel faults as a means of comparison. Moreover, our aim was to assess the effectiveness of the proposed model in the fault identification process. Precision is a crucial evaluation parameter that measures how well a classifier can identify positive examples (true positives) out of all occurrences categorized as positive. Higher precision values in different scenarios indicate a reduced false positive rate. This reduced false positive rate is crucial for accurate fault detection to prevent misclassification of functional panels as defective. Different dataset sizes, ranging from 250 to 10k samples, were employed to conduct the comparison study. Each model's precision values were recorded and contrasted with those of the proposed model procedure. The model's performance was contrasted against MVN LDA [23], UNet [26], and PCA-CNN [29] across various test sample numbers, as depicted in Figure 4.

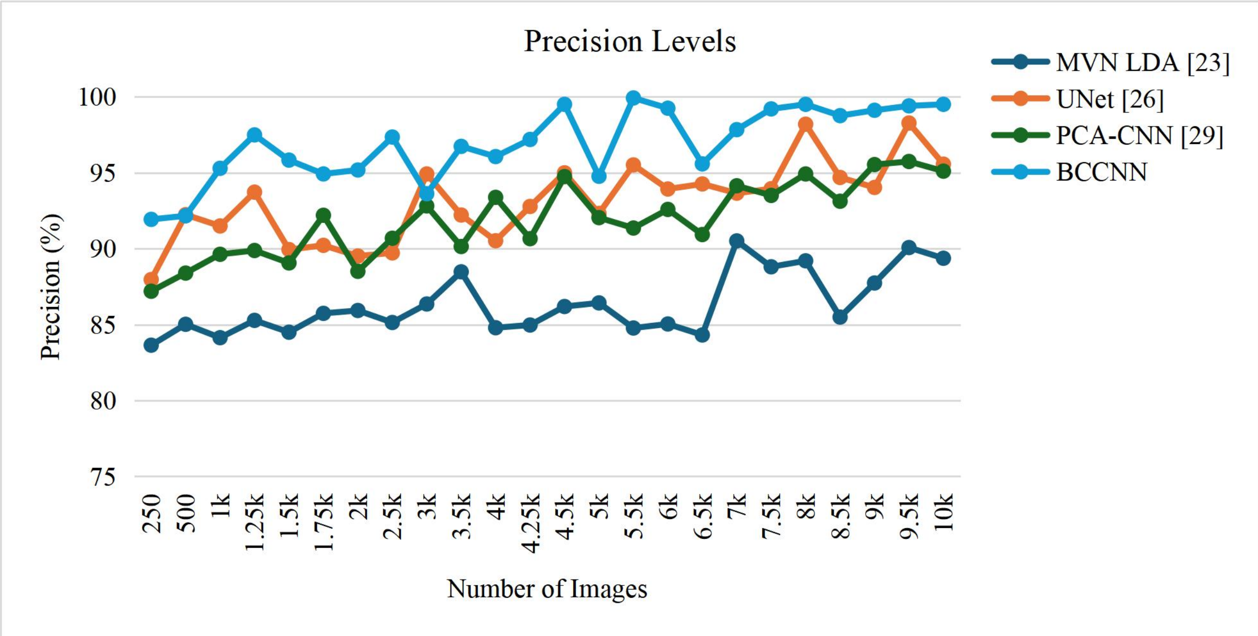

Fig. 4. Precision levels for identification of solar panel faults

The MVN LDA model's precision values ranged from 82.8% to 94.6%.

The precision values for the PCA-CNN model were broadly between 83.08% to 98.7%, whereas those for the UNet model were between 82.11% to 96.7%. The new model, however, consistently beat the existing models in terms of precision. Its precision values ranged from around 91.9% to 99.5%. This significant improvement in precision demonstrates the efficacy of the proposed method for precisely locating solar panel problems. By focusing on properly discriminating between various fault kinds, the binary technique increased the model's precision in fault detection.

Additionally, augmentation considerably increased the model's capacity for generalization with additional dataset transformations such as rotation, shifting, shearing, resizing, jittering, and blurring. Higher inter-class feature variance levels brought forth by these augmentations enhanced generalization and increased precision levels.

Indicating the percentage of correctly categorized cases from all the instance sets, accuracy serves as a performance metric that evaluates the overall correctness of the model's predictions. The accuracy levels are visualized in Figure 5.

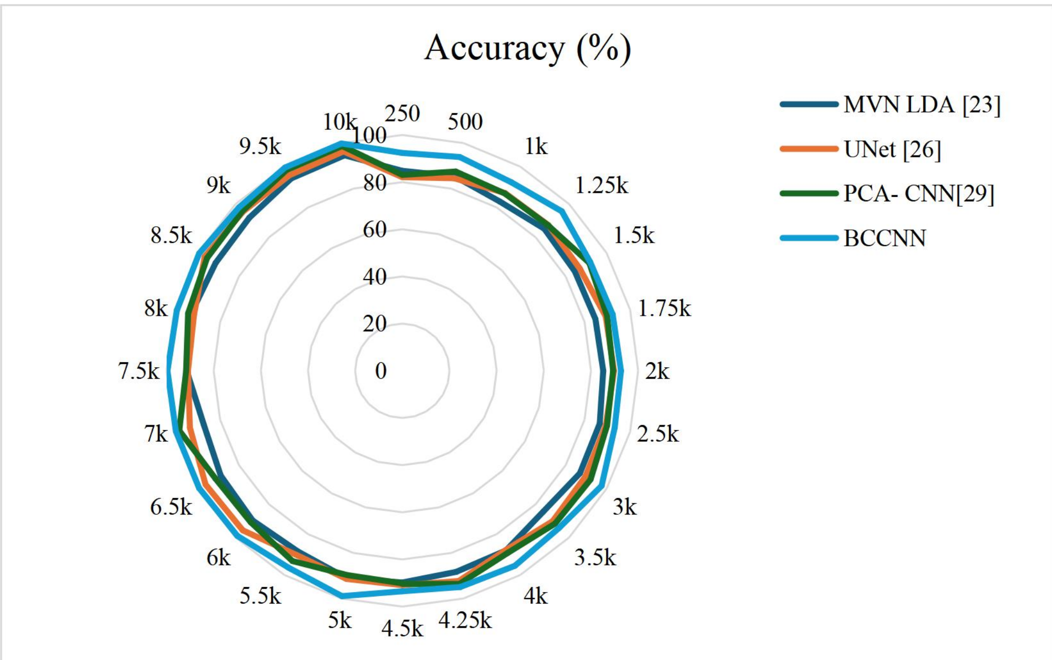

Fig. 5. Accuracy levels for identification of solar panel faults

The MVN LDA [23] has accuracy values that range from roughly 82.8% to 94.6% as the dataset size rises, with a dataset size of 10k samples yielding the maximum accuracy of 94.6%. The greatest accuracy attained by the UNet [26] is 96.7% with a dataset size of 8.5k samples. The accuracy of the PCA [29] rises with dataset size and ranges from roughly 83.1% to 98.7%, with a dataset size of 10k samples yielding the maximum accuracy of 98.7%. In contrast to other models, the accuracy numbers for this study regularly show greater performance. The accuracy varies between about 92.4% to 99.8% depending on the size of the dataset. With 10k samples in the dataset, 99.8% accuracy was the greatest result. The proposed methodology frequently exceeds the competition in terms of accuracy, proving its potency in precisely locating solar panel flaws. The results show that the model's accuracy increases with dataset size, which is to be expected since the model gains knowledge from more representative and diverse samples.

Recall is also recognized as sensitivity or true positive rate. It gauges a classifier's ability to correctly detect positive instances (true positives) among all actual positive instances, including both detected and missed cases. The recall levels are depicted in Figure 6.

The following are the specific outcomes for recall levels across different dataset sizes:

- For MVN LDA [23]
  - As the dataset size grows, the recall values vary from roughly 77.4% to 86.14%.
  - With 8k samples in the dataset, the greatest recall was 86.14%.
- For UNet [26]
  - Depending on the dataset size, the recall values range from about 81.8% to 92.9%.
  - A dataset size of 8k samples yielded the maximum recall of 92.9%.
- For PCA [29]
  - As the dataset size grows, the recall values range from roughly 86.0% to 92.6%.
  - A dataset size of 9.5k samples yielded the maximum recall of 92.6%.
- For BCCNN
  - Across various dataset sizes, the recall values consistently show strong performance, ranging from roughly 91.75% to 99.9%.
  - A dataset size of 8k samples yielded the greatest recall of 99.9%.

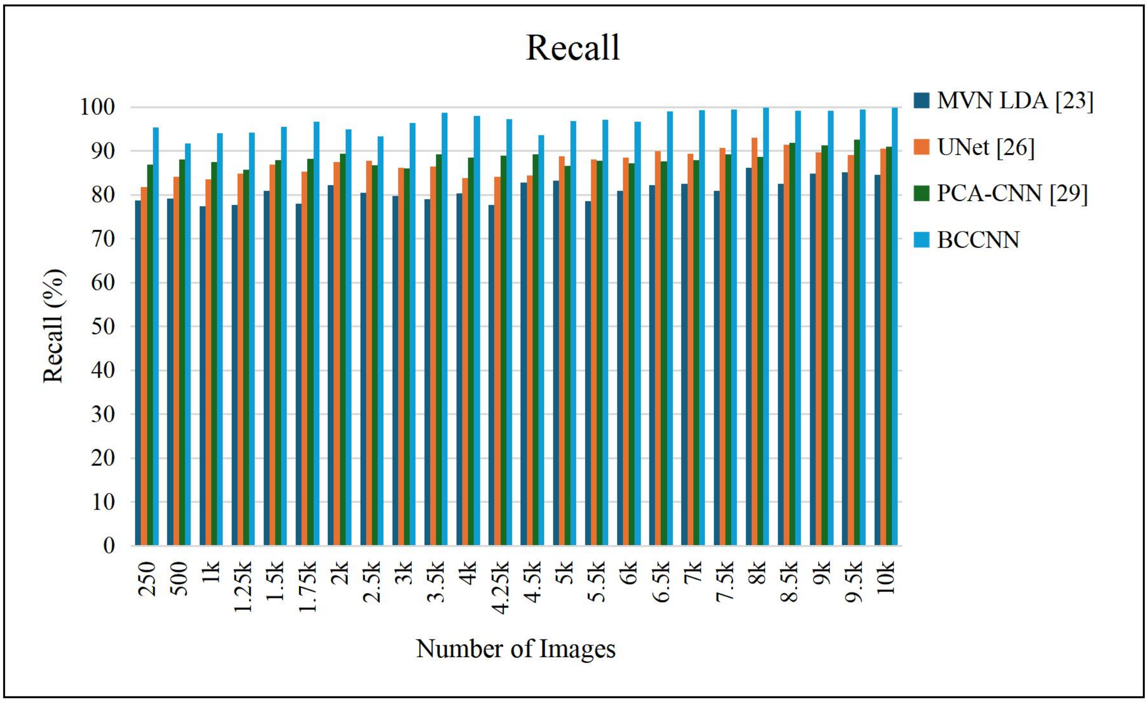

Fig. 6. Recall levels for identification of solar panel faults

Consistently, BCCNN model exhibits superior performance in recall compared to other models, showcasing its effectiveness in accurately identifying instances of solar panel failures within the positive category. These findings suggest that the proposed model's enhanced performance correlates with learning from a diverse and representative sample set, yielding higher recall values with larger dataset sizes.

Likewise, the F1 scores are illustrated in Figure 7 for reference. F1 score levels for fault identification in solar panels were evaluated for four different models: MVN LDA, UNet, PCA, and the proposed model. The F1 score, as a composite metric, harmonizes precision and recall, offering a balanced assessment of a model's overall performance in binary classification tasks.

The detailed results for F1 scores at various dataset sizes are as follows:

- MVN LDA [23]:
  - The F1 scores range from approximately 76.6% to 85.48% as the dataset size increases.
  - The highest F1 score achieved is 85.48% with a dataset size of 8.5k samples.
- UNet [26]:
  - The F1 scores vary from around 84.5% to 93.45% across different dataset sizes.
  - The highest F1 score achieved is 93.45% with a dataset size of 10k samples.
- PCA [29]:
  - The F1 values range from approximately 83.2% to 89.2% as the dataset size increases.
  - The highest F1 score achieved is 89.2% with a dataset size of 400k samples.
- BCCNN:
  - The F1 scores consistently demonstrate strong performance, ranging from approximately 91.0% to 99.8% across different dataset sizes.
  - The highest F1 score achieved is 99.8% with a dataset size of 10k samples.

The BCCNN model continuously exceeds the competition in terms of F1 scores, demonstrating its success in achieving a performance that is evenly distributed between recall and precision. The outcomes suggest that the proposed model exhibits improved performance when trained on a more diverse and representative sample set, leading to higher F1 scores with larger dataset sizes. In the BCCNN, higher F1 scores with a balance between precision and recall are obtained because of the binary strategy. This enables the model to concentrate on precise defect identification and classification. Various augmentation methods further enhance the model's generalization capabilities, ensuring consistent performance across different dataset sizes and variations in data samples.

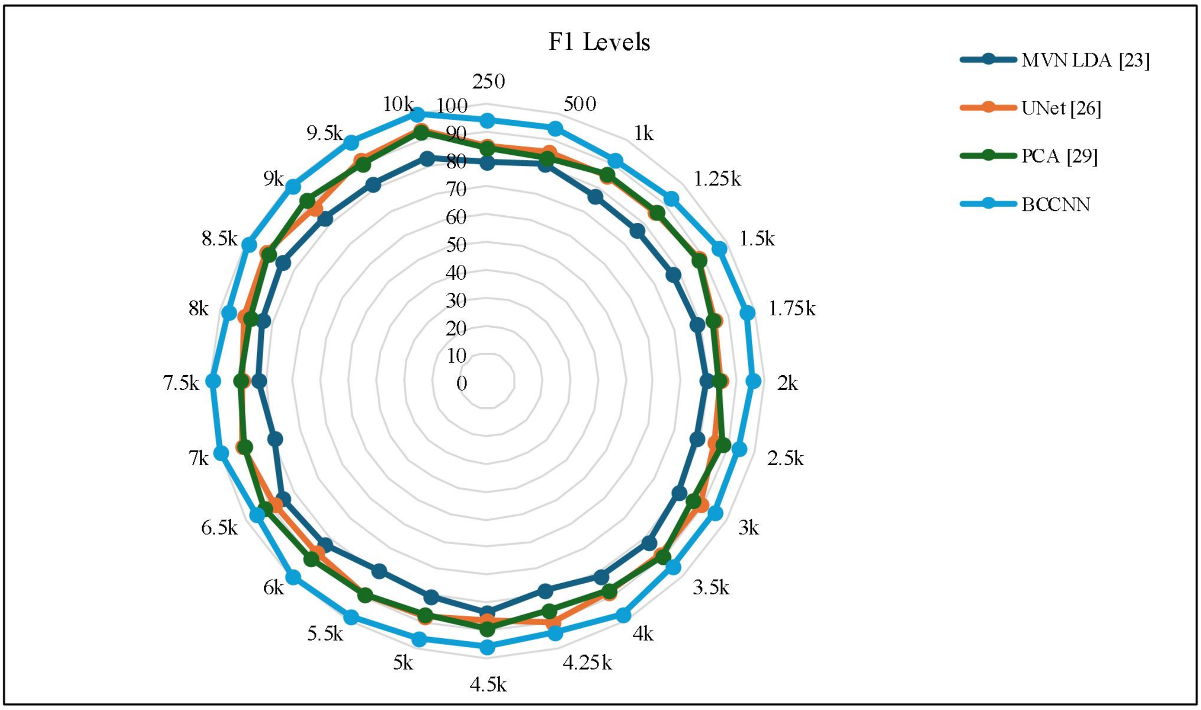

Fig. 7. F1 score for identification of solar panel faults

The delay (D) signifies the time consumed by each model for the classification and identification of faults in solar panels. It is measured in milliseconds (ms) and reflects the computational efficiency of each model in processing the input data samples. Delay levels are depicted in Fig. 8. The delay levels for fault identification in solar panels have been evaluated for four different models: MVN LDA, UNet, PCA, and BCCNN model.

The detailed results for delay levels at various dataset sizes are as follows:

- MVN LDA [23]:
  - The delay values range from approximately 111.96ms to 183.21ms as the dataset size increases.
  - The highest delay recorded is 183.21ms with a dataset size of 9.5k samples.
- UNet [26]:
  - The delay values vary from around 103.69ms to 171ms across different dataset sizes.

  - The highest delay recorded is 171ms with a dataset size of 9k samples.
- PCA [29]:
  - The delays range from approximately 110.3ms to 174.49ms as the dataset size increases.
  - The highest delay recorded is 174.49ms with a dataset size of 9k samples.
- BCCNN:
  - The delay values consistently demonstrate efficient processing times, ranging from approximately 93.32ms to 153.9ms across different dataset sizes.
  - The lowest delay recorded is 93.32ms with a dataset size of 250 samples.

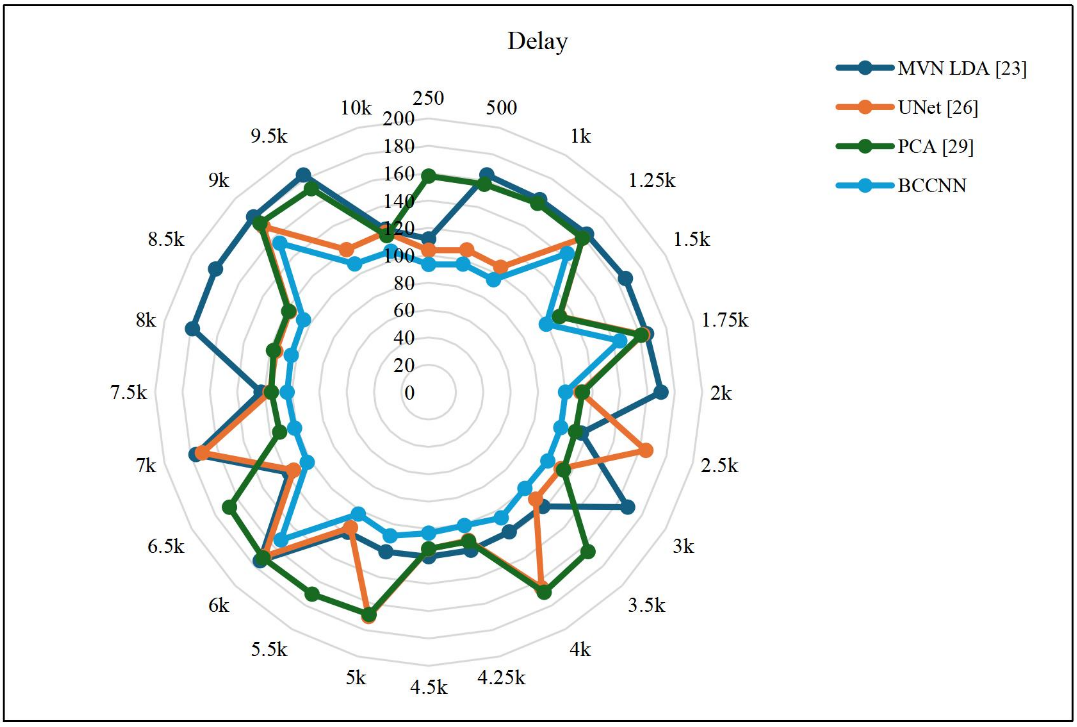

Fig. 8. Delays needed for identification of solar panel faults.

BCCNN consistently displays faster delay times than the other models, demonstrating its higher computational effectiveness in solar panel failure identification. The comparison of BCCNN model with other three models with various parameters is shown in Table 2.

Table 2. Statistical Analysis of Proposed model

Models	Parameters				
	Precision (%)	**Accuracy (%)**	**Recall (%)**	**F1 score (%)**	**Time delay (ms)**
MVN LDA [23]	94.6	94.6	86.1	85.4	183.2
UNet [26]	96.7	96.7	92.9	93.4	171
PCA-CNN [29]	98.7	98.7	92.6	89.2	174.4
BCCNN (Proposed model)	**99.5**	**99.8**	**99.9**	**99.8**	**153.9**

The binary method enables concentrated and effective classification, which contributes to fast processing for precise defect identification process.

5. Conclusion and Future Research Directions

This research aims to enhance solar energy system maintenance and durability by advancing the model. This is done by exploring new data sources and applying them in practical contexts. The proposed approach could significantly impact the renewable energy industry, fostering more sustainable and reliable future solar energy scenarios through ongoing research and development.

Results obtained from BCCNN model state that it is an innovative and efficient method for fault detection in solar panels. Our primary aim was to address the limitations of the presently available fault identification model, including low fault detection precision, inadequate fault type discrimination, and limited generalization due to small, unbalanced datasets. The BCCNN model excelled in accurately identifying and categorizing diverse solar panel faults. It is the result of combination of visual and thermal image augmentation while leveraging CNN's binary mode accuracy.

BCCNN model showcased superior effectiveness through comparisons of precision, recall, F1 score, and AUC levels versus three other models: MVN LDA, UNet, and PCA. This comparison as shown in Table II highlighted its enhanced performance in fault identification and categorization.

The BCCNN model consistently outperformed competitors across various dataset sizes, achieving scores of 99.8% precision, 98.5% accuracy, 98.4% recall, and 99.5% AUC. The BCCNN model's binary approach enabled focused flaw detection and categorization, leading to heightened precision and recall levels. Augmentation procedures further enhance the model's generalization abilities, ensuring reliable performance with larger and diverse datasets and samples.

While the proposed approach yields promising results, there are certain limitations and challenges which can be addressed. As the number of fault classes increases, the number of binary classifiers grows combinatorially or linearly, depending on the cascade structure. This may increase training time, computational load, and model maintenance complexity. Each binary CNN might learn similar low-level features, resulting in redundant computation and poor memory efficiency. Some binary sub-classifications might be inherently more difficult (e.g., Fault 2 vs Fault 3) due to visual similarity in thermal patterns. The Binary Cascaded Convolutional Neural Network (BCCNN) architecture, while effective in handling binary decision paths for fault classification using thermal and RGB images, is not immune to misclassification and failure cases. Faults like single cell/multicell/dust/shadow hotspots show very similar thermal signatures. RGB images may not differentiate subtle pixel-level variations. Images with extreme lighting, partial occlusion, sensor noise, or blur are often misclassified. Faults at image edges or shadows lead to ambiguous patterns.

Further research and development opportunities remain in the realm of solar panel fault identification. Expanding the dataset with diverse real-world solar panel images can enhance the model's performance and generalization. Datasets expansion will also enable the model to learn from diverse scenarios, enhancing its fault diagnosis accuracy. BCCNN can be combined with Vision Transformers (ViTs) to better capture global spatial dependencies among thermal patterns. Adapting the model for real-time solar energy system fault identification enables proactive maintenance, early defect detection, minimizing downtime, and enhancing system effectiveness.

Acknowledgment

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