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Fault Detection in Solar Thermal Images Using a Lightweight-CNN Architecture

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Abstract: Solar energy has been gaining significant traction as a clean, renewable energy source for the future. Each solar panel in the PV system experiences an efficiency loss of 0.5% to 1% annually. This gradual decline in performance highlights the importance of continuous condition monitoring and predictive maintenance to ensure optimal energy output. Due to abnormal temperature changes brought on by hotspots, cell cracks, bypass-diode failures, soiling, partial shading, delamination, weak electrical connections, corrosion, and PV module deterioration over time, faults may arise in the solar thermal image. Thus, a classification model is needed to differentiate between faulty and normal thermal images since it might not be visually apparent during human evaluation. In order to classify faults that might be driven by divides or hotspots in solar thermal pictures, this research suggests a new lightweight CNN classifier in the PV system that extracts the significant characteristics from the input thermal images. The model can be deployed on low-power devices because it requires fewer parameters than conventional deep networks. Because of this effective, scalable, and affordable methodology, large solar farms can now accurately diagnose PV issues. The proposed model used the MATLAB platform to compare and simulate the performance of the work. The suggested lightweight CNN outperformed the current models, CNN at 90%, DMOA at 89%, and AQO at 92%, with an accuracy value of 93% at a training percentage of 70%, according to the MATLAB validation of the planned framework. The outcomes demonstrate that the recommended approach works better than the traditional methods of solar thermal image fault detection.

Keywords: Lightweight-CNN Classifier; PV System; One-Dimensional Convolutional NN; Fault Detection; Solar Thermal Images

Nomenclature

Abbreviation	Description
PV	Photovoltaic
CNNs	Convolutional Neural Networks
ELU	Exponential Linear Unit
FPR	False Positive Rate
RELU	Rectified Linear Unit
LE	Label Encoding
AI	Artificial intelligence
ACO	Ant Colony Optimization
GWO	Gray Wolf Optimization
BFO	Bitterling Fish Optimization
AQI-DM	Aquila Inherited Dwarf Mongoose algorithm
SURF	Speed Up Robust Features
NPV	Negative Predictive Value
SIFT	Scale-Invariant Feature Transform
FDR	False Discovery Rate
SE	Squeeze-And-Excitation
1D-CNN	One-Dimensional Convolutional NN
GAN	Generative Adversarial Networks
AO	Aquila Optimization
DMO	Dwarf Mongoose Optimization
MCC	Matthews Correlation Coefficient
GLCM	Gray-Level Co-Occurrence Matrix
FNR	False Negative Rate

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1. Introduction

The use of renewable energy is growing every day to provide a clean and sustainable energy source [1]. Among all renewable options, solar energy remains the most accessible and scalable for both urban and rural applications. The utilization of solar energy has significantly increased in the last several years. The market was quickly saturated by both ground-based and rooftop technology [2]. Similar to this, solar panel preservation and operation also require attention. Although solar PV systems do not need any maintenance, however, monitoring the system is necessary to get the most out of the plants. Dust, humidity, shadow temperature, and moisture are some of the factors that impact the panel output. Monitoring individual panels in a large power plant is a difficult task [3]. These environmental influences can vary with season, geography, and installation angle, making real-time monitoring essential. However, internal resistance will result from any factors influencing solar panel yield. As a result, a thermal image of the panels will be able to promptly determine the panel's defect [4][5]. Thermal imaging provides a non-contact and efficient method for detecting irregular temperature distributions associated with faults. There are many thermal imagers on the market; however, it might be challenging to analyze individual images. PV module faults, which lower power production, can be broadly divided into two categories: transient (dust, shadow, and bird droppings) and permanent (electrical disconnection, wire losses, and aging) [6]. In order to take the necessary action, it is crucial to not only identify the defect but also determine its nature. For monitoring purposes, a lot of solar power plants currently employ manual inspection techniques [7]. For power plants with millions of PV modules spread across a vast area, this approach is not feasible [8]. The growing scale of solar farms demands automated, accurate, and low-cost fault detection systems. Such power plants have extremely high operating and maintenance costs, so the model needs an automated system that can lower these costs and improve system efficiency. CNNs have significantly improved their analysis of solar panel images since 2018 [9], [10]. These CNNs are capable of autonomously extracting features from raw image data. This makes them particularly suited for fault detection where feature variation is complex and subtle.The network is set up with several layers, often hidden layers, for the purpose of extracting features. The deeper layers target more abstract and complex features, while the initial layers concentrate on simpler features [11]. Convolutional layers for local feature extraction, pooling layers for downsampling and dimension reduction, fully-connected or global pooling layers for high-level feature extraction, and a classification layer specifically for classifying the input are the four main parts of a typical CNN [12]. While the final type of layer, the classification layer, is specialized for conducting the actual classification operation, the other three types of layers are in charge of extracting usable features [13].

Moreover, accurately classifying faults, differentiating between real defects and external factors like dirt or shading, and managing the complexity of various fault types like hotspots, cracks, and bypass diode failures are issues with solar thermal image fault detection [14]. Noise, lighting changes, and non-uniform temperature distributions further complicate this task. Another major challenge is creating reliable models that can deal with noise, changing lighting, and various fault scales [15]. In order to get around these issues, the model suggested using a lightweight CNN to identify PV panel faults. This approach ensures efficient feature learning while significantly reducing the number of trainable parameters. The following is the paper's contribution. To achieve excellent accuracy with significantly lower parameters than traditional deep CNNs, this research created a compact and computationally effective lightweight-CNN model specifically designed for thermal images of the PV system, allowing deployment on low-power edge devices. Solar panel defects, such as hotspots, cracks, bypass diode failures, delamination, and dust accumulation, can be found using the system's thermal images. On the other hand, unusual hotspots, cracks, shading, and other PV defects are properly identified with low computational cost using the lightweight-CNN, which effectively extracts temperature-based fault patterns from thermal images. Thus, the model contributes to improving operational efficiency, lowering maintenance expenses, and enhancing energy reliability.

The work is organized as follows: Section 2 provides an overview of the literature on fault detection in solar thermal pictures. Section 3 presents the proposed fault detection model using several methods. The results and discussion of the conventional and suggested methods for solar thermal image fault identification are presented in Section 4. Section 5 summarizes the work's conclusion.

2. Literature Survey

2.1. Related Work

In 2025, Tamilselvi et al. [11suggested an optimization-tuned CNN classifier to separate the significant characteristics from the input thermal images in order to classify defects produced by hotspots or cracks in solar thermal images. Their approach emphasized combining classical texture features with deep learning representations to enhance fault recognition accuracy. The input image was first pre-processed using a filtering approach to remove any noise and artifacts. With that, the features were extracted and concatenated to produce a feature vector, which the CNN classifier uses as input to detect faults. Local binary patterns, GLCM features, median binary patterns, SIFT, SURF, local directional texture patterns, and gradient local ternary patterns were among these features. By integrating handcrafted and learned features, the model achieved stronger generalization across various PV fault types. The proposed AQI-DM algorithm had the advantage of the special qualities of the Aquila and Dwarf Mongoose search agents. At 60%, 70%, and 80% training rates, the suggested AQI-DM-based CNN classifier's accuracy was 0.9207, 0.91549, and 0.89142, respectively.

In 2025, Sabati et al. [12] provided a reliable framework for PV panel fault detection that uses CNNs for feature extraction and the BFO algorithm for feature selection. The integration of bio-inspired optimization with deep learning demonstrated a significant enhancement in PV fault detection accuracy. The system integrates five pre-trained CNN architectures of GoogleNet, SqueezeNet, ResNet-50, VGGNet-16, and AlexNet with BFO to optimize feature selection and improve classification performance. The VGGNet-16 + BFO combination demonstrated extremely balanced and reliable performance, reaching the highest accuracy of 98.75%, with a high sensitivity of 98.72%, specificity of 98.78%, precision of 98.76%, and F1 score of 98.74%. Such metrics indicate a strong capability to distinguish between normal and defective modules under varying conditions.When considering total performance, BFO outperforms other optimization techniques like GWO and ACO. The integration of BFO and CNN provided balanced performance with excellent accuracy in PV panel defect identification, making it a useful method of improving the efficiency and reliability of solar systems.

In 2023, Pamungkas et al. [13] discussed that the process of maintaining optimal operating efficiency and enhancing the financial return in PV systems requires accurate fault classification. The study highlighted the limitations of conventional deep learning methods in handling unbalanced datasets and large-scale real-time applications. Previous research in this field has mostly relied on deep learning models with computational requirements, like transfer learning, which are limited by their inability to manage complicated image characteristics and unbalanced datasets. Their proposed framework sought to address this issue through architectural simplification and data augmentation. With an accuracy of 99.39%, 96.65%, and 95.72% for 2-class, 11-class, and 12-class output, respectively, the suggested lightweight coupled UdenseNet model significantly outperformed previous work in PV fault classification. Additionally, it showed improved efficiency in terms of parameter counts, which is essential for large-scale solar farm real-time monitoring. Furthermore, geometric transformation and GAN image augmentation techniques improved the model's performance on unbalanced datasets.

In 2024, Rudro et al. [14] suggested a novel deep learning model that combines the U-Net architecture with InceptionV3-Net. This hybrid design effectively merged the spatial localization capabilities of U-Net with the high-level feature extraction strength of InceptionV3. The proposed architecture improved the InceptionV3 base with ImageNet weights by using convolutional layers, SE blocks, residual connections, and global average pooling. The model is composed of a Soft-Max output layer after two dense layers with batch normalization and LeakyReLU. Incorporating photo segmentation into deep learning models significantly improves the precision and test accuracy of identifying solar panel problems. The suggested model performs outstandingly, with F1 score of 0.94, a validation accuracy of 98.34%, a precision of 0.94, a test accuracy of 94.35%, and a recall of 0.94.

In 2022, Kirubakaran et al. [15] analyzed the use of deep learning algorithms to detect these errors. Their study was among the early attempts to apply hybrid CNN architectures for PV thermal image classification. This work proposed a novel deep learning model that integrates the InceptionV3-Net and U-Net architectures. The model used an image processing technique to process the thermal image and endeavored to recognize the panel using a thermal imaging instrument. The image processing tool processed an ordinary and thermal image, demonstrating that thermal images detect hotspots. Thermal signatures were used as key indicators to identify degradation levels in panels. Similar to this, the image processing technique was used to compare the new and previous solar photovoltaic panels since any defects in the panel were identified as hot spots. Hot spots were captured in the aged panels' image, and traditional criteria were used to assess performance.

2.2. Problem Statement

The comparison of several existing techniques used for the fault detection and diagnosis of solar thermal images, considering its advantages and limitations. A critical examination of prior studies reveals that although multiple deep learning and optimization-based approaches have been explored, each method faces distinct performance and scalability challenges. The optimization-tuned CNN classifier used in Paper [11] provides high accuracy and resilience by employing AI to automatically recognize features like cracks and hotspots. However, it can be dependent on image quality and a lack of representative data, and it requires a large amount of processing power for training. Similar to this, Paper [12] employed CNNs with the BFO algorithm, which had the benefits of increased resilience and accuracy, less overfitting, real-time application potential, and flexibility to a variety of problems. The use of bio-inspired optimization significantly enhanced feature selection efficiency and improved generalization across multiple datasets. However, it also has drawbacks, including implementation complexity, computational optimization costs, data requirements, algorithm sensitivity, and interpretability. Additionally, the Coupled UDenseNet employed in Paper [13] has the advantages of training stabilization, uninterrupted gradient flow, and feature reusability, which led to accurate PV fault classification performance. The model demonstrated state-of-the-art results in classification accuracy and reduced vanishing gradient issues. In a similar vein, it also has drawbacks, such as the requirement for thorough PV fault identification and difficulties processing extremely unbalanced information in the absence of augmentation approaches. The heavy dependence on data augmentation techniques indicates that the model's performance may decline under limited or unbalanced datasets. Panel defect detection, increased precision, increased efficiency, cost savings, and resource conservation were among the advantages of Paper [14], but there were drawbacks as well, including decreased practical value, varying environmental conditions, data imbalance, and implementation complexity. Lastly, Paper [15] employs an image processing technique with the benefits of quick, non-contact inspection of huge arrays, internal problem identification, and preventative maintenance to avoid expensive damage. Its drawbacks were the requirement for specialized software and skilled workers, poor performance in specific weather situations, and difficulty detecting some surface-level flaws.

3. Proposed Methodology

Thermal anomalies, including hotspots, cracks, and connection problems, can be identified through solar thermal imaging, which is are infrared images that record the temperature distribution across the surface of solar PV modules. These anomalies often indicate local inefficiencies or electrical defects that, if undetected, can lead to long-term degradation and energy loss. However, environmental conditions during image capture, restrictions or settings of the thermal imaging equipment, and problems with the solar panels or system itself are usually the causes of defects in solar thermal images. The model suggested a novel lightweight-CNN architecture-based solar thermal image model to identify the fault in the PV panel images in order to classify these defects. The proposed system is designed to achieve a balance between accuracy, computational efficiency, and scalability for real-time deployment. In this work, the LBP-histogram is used to collect thermal images of PV modules in real-world settings. To improve thermal signatures and model generalization, the obtained images are preprocessed using noise reduction, normalization, and augmentation. Then, depth-wise separable convolution blocks are used to create a lightweight CNN architecture that effectively extracts temperature-based fault characteristics from thermal images at a lower computational cost. In order to predict faults and identify abnormalities like hotspots, cracks, and foreign material obstruction, the collected features are fed into a softmax classifier. The classifier outputs probability scores corresponding to normal and faulty conditions, ensuring interpretable fault categorization. Thus, the light-weight CNN gives the two images, such as normal images and fault images of the PV panel. The proposed model is trained and tested using annotated thermal datasets and evaluated using precision, recall, accuracy, and F1-score. The trained model is used to monitor the health of solar panels in real time on low-power devices. Fig. 1 shows the light-weight CNN-based solar thermal images fault detection model.

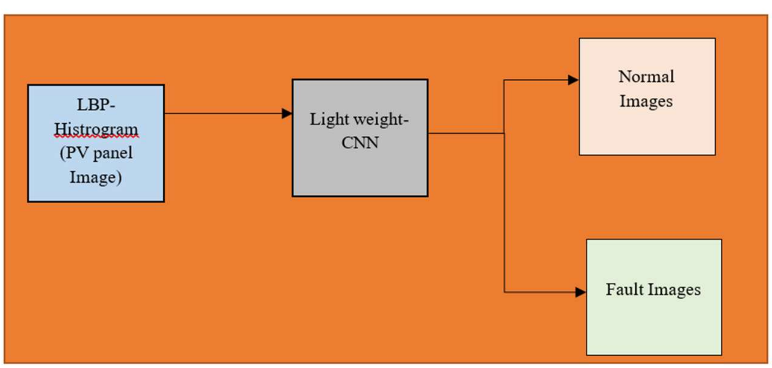

Fig. 1. *Block Diagram of the proposed fault detection of the solar thermal images model*

A. First Phase
The following steps will describe the dataset used and the preprocessing methods.

1) Dataset
The model employed the MATLAB platform from the PROMISE database for LBP-Histogram in this investigation. This database is widely recognized for its high-quality structured data and suitability for defect prediction research. While the last feature is a dependent feature that shows whether or not there is a software defect, the other 22 features can be utilized to identify software defects. Furthermore, the class distribution comprises a dataset of 3455 faults and 3537 no faults, totaling 6992 cases.

2) Preprocessing
The model in this study preprocesses the datasets to make the raw data resemble better. Data preprocessing is a crucial step to ensure consistency, accuracy, and normalization of values across multiple parameters. In this case, the model balances and normalizes using the LE and common scaler techniques. Qualitative data is measured using the LE approach. To make the data more accessible, this method provides a unique number to each category in a categorical variable, which then translates to an integer representation. This transformation facilitates numerical computation in neural network models. Furthermore, the data is scaled using the standard scaler so that the distribution is zero with a standard deviation of one. The standard variation of the model is given in Eq. (1):

$$v_{scaled} = \frac{x-\lambda}{\eta} \tag{1}$$

where µ = Mean and σ = Standard Deviation.

In the end, the model divided the dataset into 20% for testing and 80% for training. This split allows the model to learn effectively while retaining sufficient data for unbiased evaluation.

B. Second Phase (1d-Cnn)

1) Analysis of 1D-CNN for the proposed model
The 1D-CNN [16] is a unique type of ANN that extracts related features from sequential input using convolutional techniques. This makes it particularly suitable for one-dimensional data representations derived from image sequences or signal profiles. It extracts hierarchical characteristics from the input data automatically using convolutional layers. Additionally, by utilizing its capacity to capture complex dependencies within sequential code structures, it plays a critical role in improving the precision and effectiveness of software fault prediction. This layered extraction of features enhances the model's interpretability and reliability. Fig. 2 illustrates the three main layers that make up a typical 1D-CNN: 1D convolutional layers, pooling layers, and fully connected layers.

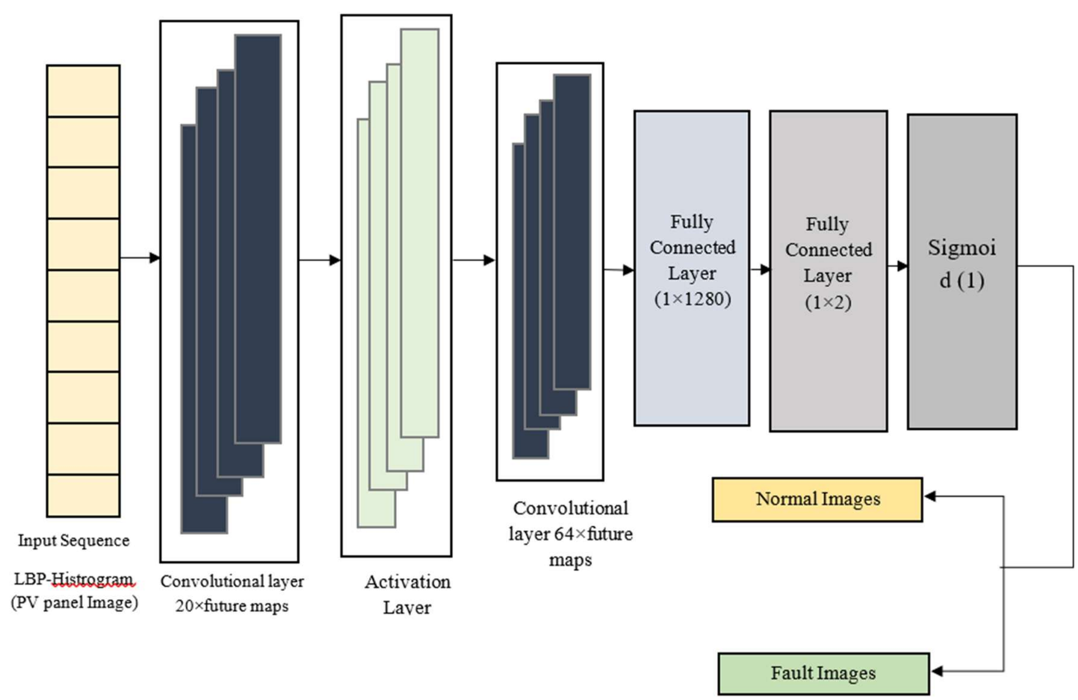

Fig. 2. *Architecture for the proposed 1D-CNN network*

In order to extract features and patterns from sequential input, the one-dimensional convolutional layer uses convolutional processes along a single axis. The one-dimensional input (vector) $x[n]$, where n varies from 0 to $N-1$, is the function's input. The total number of occurrences is N. This structure simplifies pattern recognition by focusing on temperature gradients and localized thermal variations. The layer is made using the following settings. The kernels move along the input sequence, pick up local patterns, and create output representations that draw attention to pertinent elements for more study. Let H be the one-dimensional kernel and M be the input sequence. The convolution output $\psi[n]$ can be determined by solving Eq. (2):

$$\psi[n] = (M * H)[i] = \sum_{k=0}^{H-1} M[i+k] \cdot H[k] \tag{2}$$

where $M * H$ represents the convolution process, and i is the output sequence's index. This equation mathematically defines the way features are convolved to form meaningful intermediate representations.

For 1D-CNN to learn intricate patterns in sequential data, non-linearity is introduced by an activation function. ReLU, Sigmoid, and Tanh are the most widely used functions for complex feature interactions, while there are other varieties as well. Activation functions improve the model's capability to handle complex decision boundaries. The ELU, a variation of the RELU, is the activation function that we have employed. In order to assess the function's smoothness when the input values are negative, the ELU adds an extra alpha constant (α). Furthermore, ρ is the activation function's input, and it produces more accurate results and shows a faster rate of convergence towards zero cost. $\alpha > 0$ is the formula's expression:

$$ELU(\rho) = \begin{cases} \rho & if\ \rho > 0 \\ \alpha \cdot (\exp(\rho) - 1) & if\ \rho <= 0 \end{cases} \tag{3}$$

C. Pooling Layer

A 1D-CNN's Pooling Layer reduces dimensionality and computational cost by condensing feature mappings. This reduction ensures that redundant information is minimized while retaining essential feature details. Max Pooling, which chooses the maximum value within a frame to capture the most notable features, is frequently used. Max pooling, sum pooling, and average pooling are a few types of pooling algorithms. The model used 1D max pooling in the current study, which comprises selecting the maximum value from the studied area after processing the input data using a predetermined pool size and stride.

$$\varphi_h^l = \max_{\forall p \in rh} \varphi_p^{l-1} \tag{4}$$

The way that it operates is seen in Eq. (4), where rh represents the pooling region with index h. This process ensures translation invariance, improving model robustness to spatial variations in input images.

In this suggested model's process, initially, the input PV panel image is fed into this lightweight CNN-based solar thermal image fault detection model, which generates both normal and fault images. This step automates the early detection of performance anomalies without manual inspection. The PV panel's features were first retrieved by this model. These extracted features, which are used for future tasks like defect detection and classification to identify various types of faults and feature dimensionality reduction to reduce the dimensionality of the image, represent the significant patterns and characteristics that the CNN learned from the input image. Such feature representations form the foundation for accurate and explainable fault diagnosis. Lastly, the PV panel's damaged portions or particular regions of interest can be identified by segmenting the image using the characteristics.

4. Simulation Result and Discussion

This section illustrates the effectiveness of simulation analysis for PV system fault diagnosis by contrasting the performance of the novel Lightweight-CNN-based solar thermal image analysis with existing deep learning techniques. The evaluation focuses on convergence behavior, training stability, and performance metrics such as accuracy, precision, recall, and F1-score. The MATLAB platform was used to optimize numerical data. By assessing the rate at which the suggested Lightweight-CNN attains stable accuracy during the training process, the convergence analysis for learning percentages is obtained in the results. A faster convergence rate indicates an improved learning mechanism and better generalization capability. The outcomes demonstrate that the suggested model's streamlined design and effective feature extraction capacity result in better learning percentages and quicker convergence. However, based on solar thermal images, the proposed lightweight CNN classifier is utilized in this model to precisely detect and categorize PV system defects. When the performance of the proposed lightweight CNN classifier is compared using the previously mentioned performance indicators, it is demonstrated to perform better than the conventional approaches. Hence, the proposed model ensures computational efficiency without compromising diagnostic accuracy.

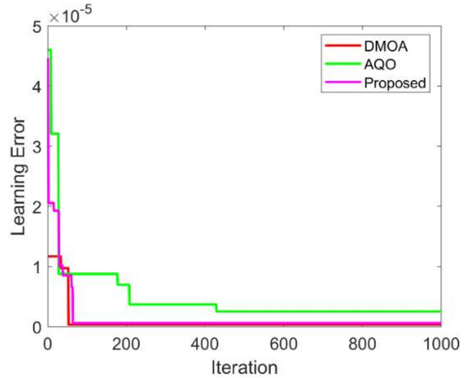

Fig. 3. *Convergence analysis at 60% of training*

In the convergence analysis of the proposed model, the study on convergence linked to fitness employing the proposed lightweight-CNN approach over the earlier approaches. Convergence analysis helps in evaluating how quickly the model reaches minimal error values across training cycles. The investigation uses iterations between 10, 20, 30, 40, and 50. The convergence analysis of the proposed model at 60% of training is shown in Fig. 3. In this analysis, the proposed lightweight-CNN model achieved an error value of 205.768 when the training rate was 60%, whereas the current methods, such as DMOA and AQO, reached values of 116.964 and 320.632, respectively, within the tenth cycle. Although the proposed method shows slightly higher error at 60%, its stability over multiple iterations indicates robustness in learning convergence.

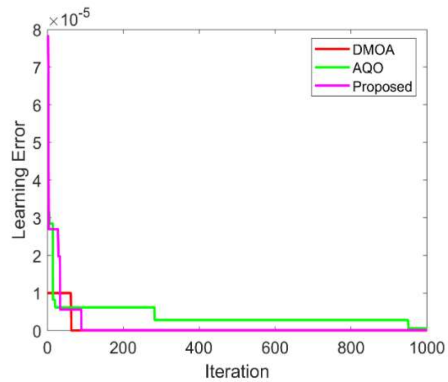

Fig. 4. *Convergence analysis at 70% of training*

The convergence analysis of the proposed model at 70% of training is shown in Fig. 4. The increased training percentage demonstrates how model learning progresses with larger data exposure. In this analysis, the proposed lightweight-CNN model achieved a minimal error value of 205.768 when the training rate was 70%, whereas the existing methods, such as DMOA, achieved 99.7856 and AQO reached 81.6273, respectively, within the tenth cycle.

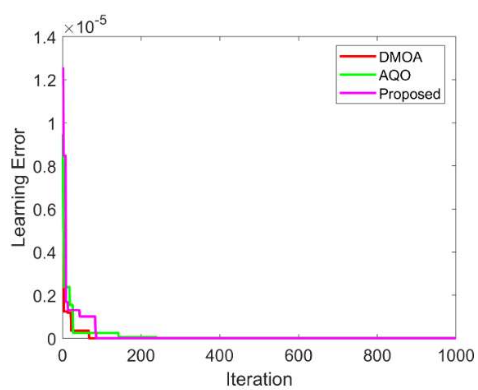

Fig. 5. *Convergence analysis at 80% of training*

The convergence analysis of the proposed model at 80% of training percentage is shown in Fig. 5. This phase evaluates how the model performs when exposed to maximum training data for improved generalization. In this analysis, at an 80% training rate, the proposed lightweight-CNN model obtained an error value of 1307.86, despite the DMOA reaching the error value of 355.849 and the AQO achieving the error value of 252.496 in the 30th iteration, respectively. While the error values vary, the lightweight-CNN displays consistent adaptability across different iterations, suggesting enhanced resilience to training fluctuations. Consequently, the outcomes demonstrate that the suggested approach aligns with the optimal outcome for multi-objective challenges. As a result, the overall evaluation demonstrates that the suggested method contributes to better convergence results.

However, the performance of the proposed lightweight CNN classifier for fault detection in solar thermal images, in contrast with traditional methods including CNN, DMOA, and AQO at 60%, 70%, and 80% training percentage, is given in the table below. This comparison validates how the proposed architecture performs across diverse metrics and training conditions. In this table, the proposed Lightweight CNN classifier is compared with existing models.

Table 1. *Comparison of the suggested lightweight CNN's performance vs* **THE** *existing method at 60% of training percentages*

Training Percentage lp=60%				
Metrices	**CNN**	**DMOA**	**AQO**	**Lightweight CNN**
Accuracy	91%	93%	92%	84%
Precision	91%	92%	91%	78%
Sensitivity	93%	94%	92%	92%
Specificity	96%	97%	96%	95%
F1Score	92%	93%	91%	82%
MCC	88%	90%	87%	76%
NPV	96%	97%	96%	95%
FPR	4%	3%	4%	5%
FNR	7%	6%	8%	8%
FDR	9%	8%	9%	22%

Table 1 shows the comparison of the suggested lightweight CNN's performance vs **THE** existing method at 60% training percentages. The proposed model exhibits slightly lower accuracy but maintains competitive sensitivity, showing it detects most fault instances correctly. At a training percentage of 60%, the proposed lightweight CNN attained the FDR value of 22% which is higher than the existing models, such as CNN of 9%, DMOA of 8%, and AQO of 9%, respectively. However, for the F1 score analysis, the AQI-DM-based lightweight CNN attained the value of 82%, and the existing models, such as CNN of 92%, DMOA of 93%, and AQO of 91%, respectively.

Table 2. *Comparison of the suggested lightweight CNN's performance vs* **THE** *existing method at 70% of training percentages*

Training Percentage lp=70%				
Metrices	**CNN**	**DMOA**	**AQO**	**Lightweight CNN**
Accuracy	90%	89%	92%	93%
Precision	88%	92%	93%	91%
Sensitivity	94%	85%	92%	92%
Specificity	97%	94%	96%	97%
F1Score	90%	88%	92%	91%
MCC	87%	83%	89%	88%
NPV	97%	94%	96%	97%
FPR	3%	6%	4%	3%
FNR	6%	15%	8%	8%
FDR	12%	8%	7%	9%

Table 2 shows the comparison of the suggested lightweight CNN's performance vs **THE** existing method at 70% training percentages. AT THIS STAGE, THE PROPOSED MODEL ACHIEVES BETTER OVERALL ACCURACY AND SPECIFICITY, CONFIRMING IMPROVED LEARNING FROM A LARGER TRAINING **SET.** At a training percentage of 70%, the proposed lightweight CNN attained the accuracy value of 93% which is higher than the existing models, such as CNN of 90%, DMOA of 89%, and AQO of 92%, respectively. However, for the F1 score analysis, the proposed lightweight CNN attained the value of 91%, and the existing models, such as CNN of 90%, DMOA of 88%, and AQO of 92%, respectively. Thus, the proposed CNN shows high adaptability and steady classification consistency across performance indicators.

Table 3. *Comparison of the suggested lightweight CNN's performance vs* ***THE*** *existing method at 80% of training percentages*

Training Percentage lp=80%				
Metrices	**CNN**	**DMOA**	**AQO**	**Lightweight CNN**
Accuracy	91%	88%	89%	85%
Precision	90%	82%	88%	81%
Sensitivity	94%	91%	89%	86%
Specificity	97%	95%	95%	94%
F1Score	91%	85%	88%	82%
MCC	88%	80%	83%	76%
NPV	97%	95%	95%	94%
FPR	3%	5%	5%	6%
FNR	6%	9%	11%	14%
FDR	10%	18%	12%	20%

Table 3 shows the comparison of the suggested lightweight CNN's performance vs **THE** existing method at 80% training percentages. **THE ACCURACY SHOWS A SLIGHT DECLINE, WHICH MAY BE DUE TO OVERFITTING DURING HIGH TRAINING EXPOSURE.** At a training percentage of 80%, the proposed lightweight CNN attained the FPR value of 6% which is higher than the current models, such as the CNN of 3%, DMOA of 5%, and AQO of 5%, respectively. However, for the specificity analysis, the proposed lightweight CNN attained the value of 94%, and the existing models, such as CNN of 97%, DMOA of 95%, and AQO of 95%, respectively. This shows that the lightweight CNN remains competitive, offering acceptable trade-offs between accuracy and computational load. Thus, the proposed lightweight CNN classifier displays superior performance when compared to CNN, DMOA, and AQO, establishing its effectiveness and robustness.

5. Conclusion

In this paper, the model proposed a novel light-weight CNN based solar thermal images for detecting faults in solar the images of the PV system. The approach emphasizes computational efficiency, ensuring that the fault detection process can be implemented on embedded or edge devices with limited resources. In this model, the normal and defective solar thermal images were created by sending the data from the PV panel image into a lightweight CNN. In a lightweight CNN structure, the convolution, pooling, activation, and fully-connected layers were used to process the lightweight CNN in order to extract characteristics and categorize the outcome as either normal or defective. In a similar vein, the suggested lightweight CNN model effectively extracts significant characteristics from thermal images with minimal computing complexity, which qualifies it for real-time fault detection applications. This makes the proposed system an ideal candidate for autonomous fault detection in large distributed PV systems. In comparison to traditional deep learning models, simulation and experimental assessments show that the approach produced excellent accuracy, quicker convergence, and shorter processing times. As a result, the suggested approach at the 20^{th} iteration achieves a minimum value of 269.6, whereas the current DMOA achieved 99.7856 and AQO reached 81.6273, respectively, at the 70% training rate. Also, even though the DMOA reached 355.849 and the AQO achieved 252.496, the suggested technique in the 30th iteration reached a value of 1307.86 when the training rate is 80%. The findings demonstrated that the suggested lightweight CNN model offered a reliable and efficient way to improve PV system maintenance and operating performance. Overall, the proposed approach not only enhances diagnostic accuracy but also supports proactive maintenance strategies for renewable energy infrastructure. Future research could concentrate on expanding this method to large-scale PV installations for real-time fault diagnosis and integrating it with IoT-based monitoring platforms.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

References

[1] Duranay, Z.B. "Fault detection in solar energy systems: A deep learning approach." Electronics 12, no. 21 (2023): 4397.

[2] Korkmaz, D. and Acikgoz, H. "An efficient fault classification method in solar photovoltaic modules using transfer learning and multi-scale convolutional neural network." Engineering Applications of Artificial Intelligence 113 (2022): 104959.

[3] Ramadan, E. A., Moawad, N.M., Abouzalm, B.A. Sakr, A.A. Abouzaid, W.F. and El-Banby, G.M. "An innovative transformer neural network for fault detection and classification for photovoltaic modules." Energy Conversion and Management 314 (2024): 118718.

[4] Abdelsattar, M., Abdelmoety, A., Ismeil, M.A. and Emad-Eldeen, A. "Automated defect detection in solar cell images using deep learning algorithms." IEEE Access (2025).

[5] Jumaboev, S., Jurakuziev, D. and Malrey Lee. "Photovoltaics plant fault detection using deep learning techniques." Remote Sensing 14, no. 15 (2022): 3728.

[6] Venkatesh, S. Naveen, B. Jeyavadhanam, R., Sizkouhi, A.M.M., Esmailifar, S. M., Aghaei, M. and Sugumaran, V. "Automatic detection of visual faults on photovoltaic modules using deep ensemble learning network." *Energy Reports* 8 (2022): 14382-14395.

[7] Sridharan, N. V., and Sugumaran, V. "Convolutional neural network based automatic detection of visible faults in a photovoltaic module." Energy Sources, Part A: Recovery, Utilization, and Environmental Effects 47, no. 1 (2025): 6270-6284.

[8] Selvaraj, T., Rengaraj, R., Venkatakrishnan, G.R., Soundararajan, S.G., Natarajan, K., Balachandran, P.K., David, P.W., and Selvarajan, S. "Environmental fault diagnosis of solar panels using solar thermal images in multiple convolutional neural networks." *International Transactions on Electrical Energy Systems* 2022, no. 1 (2022): 2872925.

[9] Baltacı, Ö., Kıral, Z., Dalkılınç, K. and Karaman, O. "Thermal image and inverter data analysis for fault detection and diagnosis of PV systems." *Applied Sciences* 14, no. 9 (2024): 3671.

[10] Segovia Ramírez, I., and Márquez, F. P. G. "Machine learning for fault detection and diagnosis of large photovoltaic plants through internet of things platform." *SN Computer Science* 5, no. 1 (2023): 8.

[11] Tamilselvi, T., Ramaprabha, R. and Sathies Kumar, T. "Fault detection in solar thermal images using Convolutional neural network and hybrid optimization approach." *Environmental Progress & Sustainable Energy* (2025): e70035.

[12] Sabati, A., Bayindir, R. and Rahebi, J. "Photovoltaic Panels Fault Detection with Convolutional Neural Network and Bitterling Fish Optimization (BFO) Algorithm." *International Journal of Computational Intelligence Systems* 18, no. 1 (2025): 239.

[13] Pamungkas, R. F., Utama, I.B.K.Y. and Jang, Y.M. "A novel approach for efficient solar panel fault classification using coupled udensenet." *Sensors* 23, no. 10 (2023): 4918.

[14] Rudro, R. A. M., Nur, K., Sohan, M.F.A.A., Mridha, M.F., Alfarhood, S., Safran, M. and Kanagarathinam, K. "SPF-Net: Solar panel fault detection using U-Net based deep learning image classification." *Energy Reports* 12 (2024): 1580-1594.

[15] Kirubakaran, V., Preethi, D. M. D., Arunachalam, U., Rao, Y.K.S.S., Gatasheh, M.K., Hoda, N. and Anbese, E.M. "Infrared thermal images of solar PV panels for fault identification using image processing technique." *International Journal of Photoenergy* 2022, no. 1 (2022): 6427076.

[16] Begum, M., Shuvo, M.H., Nasir, M.K., Hossain, A., Hossain, M.J., Ashraf, I., Uddin, J. and Samad, M. A. "LCNN: lightweight CNN architecture for software defect feature identification using explainable AI." *IEEE Access* 12 (2024): 55744-55756.