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Enhanced Solar Panel Segmentation and Hotspot Recognition Using U-Net: A Multiclass Semantic Segmentation Approach

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***Abstract*—Maintaining and optimising photovoltaic (PV) systems requires accurate segmentation and detection of thermal hotspots in solar panels. This study present a novel multiclass semantic segmentation approach based on a U-Net deep learning model to help solar panel and hotspot analysis. Utilising the U-Net architecture, solar panels, hotspots, and background components can be classified with high fidelity. A large dataset of thermal images with multiple class labels was rigorously trained and evaluated on the model. The U-Net model also achieved a very impressive overall accuracy of 97.96% and an average Intersection over Union (IoU) of 0.7246 on all classes. In particular, it recorded an IoU score of 0.9485 for background, 0.9677 for the solar panels, and 0.2578 for the hotspots. The model does well at separating background from solar panels, but lower IoU for hotspots suggests that defining areas with solar panels is more challenging, as they are smaller and less obvious. The results show how the U-Net model increases the fault detection accuracy in PV systems by accurately segmenting the components of the solar panel and the hotspots. Insights from these studies will lead to improved maintenance practices that can increase the operational lifespan of solar installations. By doing so, this study highlights the potential of deep learning models, particularly U-Net, to facilitate solar panel analysis and ultimately contribute to more reliable and sustainable energy production through the automation of monitoring and maintenance in solar power plants, with scalability and efficiency.**

***Index Terms*—Solar Panel, Semantic Segmentation, Hotspot Recognition, U-Net, Deep learning.**

I. INTRODUCTION

As renewable energy becomes progressively demanded worldwide, solar power is becoming a necessary technology in the transition to a sustainable energy system. Solar energy generation is a foundation of the PV panels and therefore needs monitoring and maintenance on a continuous basis [1][2]. Early detection of defects, such as thermal hotspots, is a major challenge in managing PV systems [3][4]. Manual inspections and simple thermal imaging are both labour-intensive, time-consuming, and error-prone and are unsuitable for dependable monitoring.

Solar panel maintenance is important because it is essential to maintain the maximum performance and life of a solar energy system. Maximising energy production requires regular upkeep, as dust, debris, and environmental pollutants can severely reduce a panel's efficiency. In this context, one specific challenge is the development of thermal hotspots, where certain parts of a solar panel get too hot because of bad connections or defects inside the cells [5][6]. If left unattended, these hotspots can cause a loss of energy output and even permanent damage to the panels.

New opportunities in the automatic analysis of solar panel images have become available through recent advancements in machine learning and computer vision. Semantic segmentation is one of many ways to do detailed image analysis, in which each pixel in an image is classified into a set of pre-defined categories [7]. There have been many architectural designs for such purposes, but the U-Net model has become popular as it can generate high-resolution segmentation even when trained on a small dataset.

This study is centred on advancing the segmentation of solar panels and enhancing the detection of thermal hotspots through a U-Net-based multiclass semantic segmentation framework. The segmentation task encompasses three distinct categories: background, solar panels, and hotspots. Unlike binary segmentation approaches, this multiclass method enables simultaneous analysis of these critical components within a single image, providing a clear distinction among the classes. Achieving high performance hinges on the model's ability to accurately identify and localise hotspots within the complex structure of solar panels and to effectively separate the panels from their surroundings.

This research leverages the capabilities of the U-Net architecture to produce insights from a dataset of thermal images collected from operational solar PV systems. The primary goal is to develop a model that not only distinguishes solar panels from their background but also accurately detects hotspots that may signal potential faults or inefficiencies. This

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integrated approach aims to support the automatic monitoring and maintenance of solar power installations.

The study's contributions are threefold. First, it introduces an innovative application of the U-Net model for multiclass semantic segmentation within the context of solar energy analysis. Second, it demonstrates how this approach enhances hotspot detection accuracy, benefiting PV system management. Lastly, it provides a thorough assessment of the model's performance, including its practical implications for real-world applications.

The structure of this paper is as follows: Section 2 reviews prior work on solar panel segmentation and hotspot detection. Section 3 details the methodology, including the dataset, model architecture, and training procedures. Section 4 presents and discusses the experimental results. Section 5 concludes the paper and suggests directions for future research.

II. Review of Related Works in Solar PV Segmentation and Hotspot Detection

In recent years, the analysis of solar panels, particularly in segmentation and defect detection, has intensified alongside the rapid expansion of PV system installations. This section provides an overview of recent advancements in solar panel segmentation and hotspot detection, spanning from traditional image processing techniques to cutting-edge deep learning methods.

The classical image processing techniques, such as thresholding, edge detection, and morphological operations, were used in early efforts in solar panel segmentation. For example, A. Shaik et al. [8] used a combination of edge detection and region growing to segment solar panels from aerial images. Though these methods were successful in controlled environments, performance on variable lighting, shadows, and complex backgrounds was hampered by the resulting poor quality of segmentation results.

Since the arrival of deep learning, convolutional neural networks (CNNs) [9] have become the standard technique to perform image segmentation tasks, including the segmentation of solar panels. The recent studies showed that CNN-based models outperform the traditional techniques, especially in the case of solar panel images that have complex patterns and textures. U-Net [10] is a leading architecture for semantic segmentation among these models, largely due to its distinctive structure, which localises features across diverse scales.

According to M. Arif Wani et al. [11], for instance, a deep learning model was used to segment solar panels in satellite imagery with greater accuracy than conventional methods. J. Camilo et al. [12] had also applied a CNN architecture to perform pixel-wise classification of PV panels from high-resolution images and shown that the model generalises well across different solar PV array aerial imagery datasets.

Efficiency and longevity of solar panels are directly related to the successful identification of hotspots in PV systems. Historically, hotspot detection was a result of thermal imaging coupled with manual inspection [13][14]. These methods were useful, but they were often time-consuming and depended heavily on the operator's expertise. Additionally, human error is common in manual inspection of large-scale solar farms.

Recently, hotspots have been automatically detected using machine learning techniques. First, feature extraction methods combined with early machine learning models (e.g., support vector machines (SVM), random forest) were used to make the initial approaches. As an example, R. O. Serfa Juan et al. [15] developed a way to classify normal and defective solar cells based on the electroluminescence (EL) imaging coupled with some digital image processing techniques and an SVM-based classifier. Nevertheless, these approaches required extensive feature engineering, and the quality of the extracted features was not always optimal.

Hotspot detection in the PV systems has been greatly helped by the advent of deep learning, specifically CNNs. CNNs allow us to learn hierarchical features without manual feature extraction and automatically from raw image data. For example, M. Vlaminck et al. [16] proposed a CNN-based method for anomaly detection of PV power plants from aerial imagery that outperforms other machine learning approaches in terms of both accuracy and robustness.

Recent research has since focused on pixel-level hotspot detection using fully convolutional networks (FCNs) [17] and U-Net architectures [10]. To segment hotspots in thermal images, Y. Shen et al. [18] used a modified U-Net model that results in state-of-the-art accuracy and precise localization. Indeed, this method was particularly successful for detecting small, scattered hotspots that are difficult to discern using standard approaches.

Similar to this, X. Hao et al. [19] proposed a U-Net-based model for multi-objective semantic segmentation, an approach that makes feature recognition more efficient in large and complex datasets such as unmanned aerial vehicle (UAV) remote sensing in construction zones. They showed that the model performs well for intricate segmentation across multiple classes. This body of work serves as inspiration for the current work that extends U-Net application to solar panel analysis, for simultaneous segmentation of solar panels, hotspots, and background elements in a single framework.

In contrast to previous research that employed separate deep learning models such as You Only Look Once (YOLO) [20], Single Shot MultiBox Detector (SSD) [21] or others for object detection and segmentation tasks separately, this study improves segmentation accuracy by performing thermal hotspot detection within the same U-Net architecture. To simplify the process and to reduce computational demands and time, the proposed unified U-Net model simplifies the process by eliminating the need for multiple models. This is a major leap forward for the field, enabling more efficient monitoring and maintenance of solar energy systems. Furthermore, although existing models have successfully addressed the problem of solar panel segmentation and hotspot detection separately, this work bridges the gap between these two by combining them through multiclass semantic segmentation.

III. Methodology

In this section, the methodology for developing and evaluating the U-Net-based multiclass semantic segmentation model for solar panel segmentation and hotspot detection is described. The methodology is structured into several essential components: This includes dataset preparation, model architecture, training procedures, and performance evaluation metrics. Fig. 1 illustrates a visual representation of the framework for the semantic segmentation approach, comprised of the segmentation of solar PV panels and hotspot recognition.

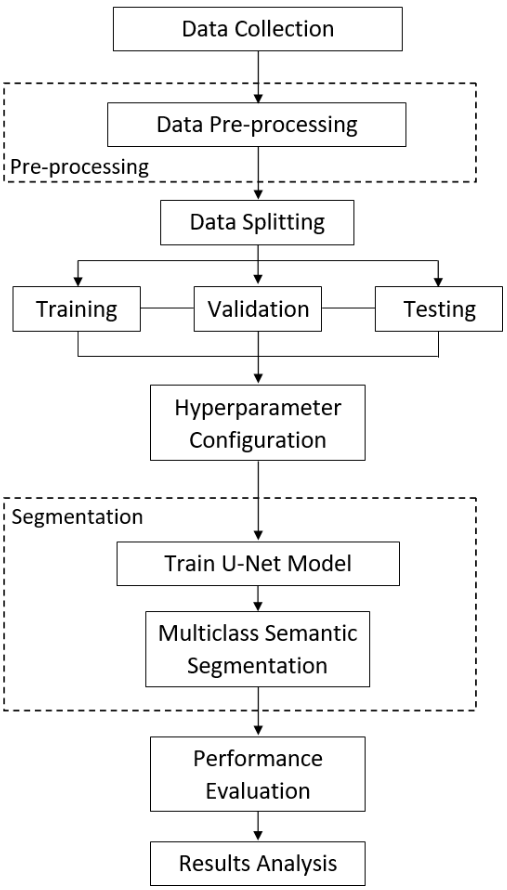

Fig. 1. The methodology framework for semantic segmentation tasks to segment PV panels and recognition of hotspots.

A. Data Collection and Preparation

In this study, thermal images from active PV systems are used in a dataset. Thermal cameras mounted on drones and ground-based platforms were used to image large PV installations from a 15-meter height, yielding complete coverage. Data acquisition occurred under a variety of environmental conditions, mainly during sunny periods with irradiance of 508 W/m², including recording thermal patterns in both standard and defective panel operation.

Furthermore, images from PV farms in Kelantan, Malaysia, were sourced with different panel types and configurations to increase dataset diversity. This collection effort was comprehensive, producing over 670 annotated thermal images, each painstakingly annotated to identify areas of interest for multiclass semantic segmentation.

The dataset classifies each image into three categories: solar panel, background, and hotspot. After preprocessing the images and labels, they were used to train the U-Net model. To solve this challenging segmentation task, precise boundary distinctions were made for the solar panel and hotspots, accounting for the complex shapes and variable sizes of hotspots while maximising segmentation accuracy.

Data augmentation techniques were used to improve the robustness and the generalisation capability of the models. Images were randomly transformed, which included rotations, flips, scaling, and cropping. It is notable that this augmentation process was especially important for increasing the number of hotspot instances, which are generally sparse and exhibit major variability in size and shape.

B. Implemented Model Architecture and Training Configuration

The U-Net architecture [10] is the core of this study's methodology, which is a fully convolutional network that can generate pixel-level segmentations. This model was selected due to its ability to represent both broad contextual information and fine image details, which is well suited to the multiclass segmentation tasks that address in this study.

The U-Net architecture is composed of contracting (encoder) paths and expanding (decoder) paths. On the contracting path, convolutional and max pooling layers are used, reducing spatial dimensions and increasing feature depth at the same time. On the other hand, the expanding path gradually upsamples these feature maps and merges with high-resolution features from the contracting path via skip connections so that the network retains critical spatial information at all levels [10].

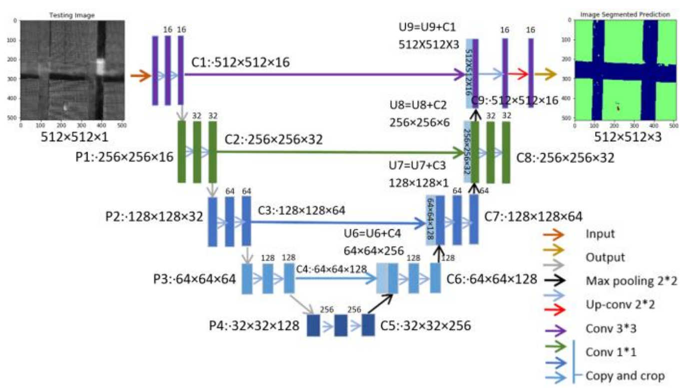

Fig. 2. The implemented U-Net model architecture.

The basic U-Net design used in this work was modified to fit our particular use case, as illustrated in Fig. 2:

1) Input layer

The input to the model was thermal images of size 512×512 pixels. These images were resized from their original dimensions of 312×234 to this input size.

2) Encoder

It had five convolutional blocks with two convolutions followed by pooling. In the first block, there are 16 filters, which double at each block from there.

3) Bottleneck layer

The bottleneck layer at the centre of the U-Net receives the most abstracted features before they are unsampled.

4) Decoder

The encoder and decoder match: each upsampling is concatenated with the corresponding encoder feature map followed by two convolutional layers. This structure allows the model to reconstruct the spatial resolution without losing the features learnt.

5) Output layer

The final layer employs a softmax activation function to generate a pixel-wise classification, assigning each pixel to one of three categories: solar panel, background, or hotspot.

Model training was conducted on a high-performance computing setup equipped with an NVIDIA GeForce RTX 3050 GPU (4GB memory) and 16GB RAM. It was developed based on TensorFlow 2.4.0 and Keras 2.4.3. Hyperparameters used for training the U-Net model for semantic segmentation are given in Table I. In the case of the class imbalance of the hotspot dataset, hotspots are rare and small; therefore, a weighted categorical cross-entropy loss function was used. To increase the sensitivity of the model to the hotspot class, higher weights were given to those regions that are critical. Adam Optimiser was used for training using an initial learning rate of 0.001 and a decay learning rate schedule to reduce the rate to prevent overfitting and allow stable convergence.

TABLE I . HYPERPARAMETER TUNING OF TRAINING MODEL

Hyperparameter/ Configuration	Descriptions
Input image size	[512, 512]
No. of classes	Class 1: Background Class 2: PV Panel Class 3: Hotspot
Optimizer	Adaptive Moment Estimation (Adam)
Learning rate	0.001
No. of epochs	100
Batch size	1
Loss function	Categorical cross-entropy
Data splitting	80% (Training); 10% (Validation); 10% (Testing)

Model performance was optimised through the training process structured in stages. The dataset was split into three subsets: 80% for training, 10% for validation, and 10% for testing. By separating it into two parts, it could efficiently evaluate the model on unseen data and still generalise well. Although GPU memory limits permitted a batch size of 1, the model was trained for over 100 epochs with early stopping on validation loss to prevent overfitting. For training, real-time data augmentation was used to make the model more resilient to input data variation, and input images were normalised to the [0, 1] range.

C. Evaluation Metrics

Several metrics used in standard segmentation tasks were used to evaluate the performance of the model.

1) Pixel Accuracy (PA)

PA is the proportion of correctly classified pixels (true positives and true negatives) total. It is a general representation of how good the model does in all classes but could be deceptive in case of class imbalance imbalance [10][18].

$$PA = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Where;

TP: True Positives (correctly predicted positive pixels)
TN: True Negatives (correctly predicted negative pixels)
FP: False Positives (incorrectly predicted positive pixels)
FN: False Negatives (incorrectly predicted negative pixels)

2) Intersection over Union (IoU)

Overlap between the predicted and ground truth segments was computed for each class using IoU [10][18]. This metric is very good for evaluating how well the model can recognise and localise some classes, like hotspots.

$$IoU = \frac{TP}{TP + FP + FN} \quad (2)$$

Where;

TP: True Positives (pixels accurately identified as belonging to the target class)
FP: False Positives (pixels mistakenly classified as belonging to the target class)
FN: False Negatives (pixels that are part of the target class but were not identified as such)

3) Mean Intersection over Union (mIoU)

Mean IoU is the average of IoU values across all classes. It provides a full measure of the model performance over all classes [10][18]. When we want to look at a multiclass segmentation task, the mIoU is useful because it provides a performance on all classes, including less frequent or smaller classes such as hotspots.

$$mIoU = \frac{1}{N}\sum_{i=1}^{N} IoU_i \quad (3)$$

Where;

N: The total number of classes
IoU_i: IoU for class i

IV. RESULTS AND DISCUSSION

In this study, a comprehensive evaluation of the training dynamics and performance metrics of the U-Net model [10] for multiclass segmentation of thermal images in solar PV systems is presented. The study analyses the observed training process to show how the model is precise in distinguishing different classes and how it can learn and make changes to predictions over time. Finally, these evaluations show that the model is generalisable to unseen data, specifically its ability to find critical areas, such as hotspots.

The loss curve is shown in Fig. 3 for training and validation over 100 epochs. The model has to struggle to learn the underlying patterns in the data, so the initial losses are both high. Yet it can see a steep drop in loss values after the first 10 epochs, indicating the model is quickly learning and adapting to the key features.

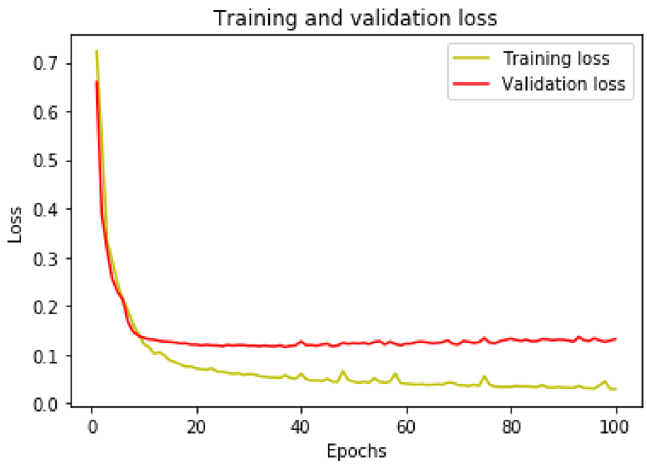

Fig. 3. Training and validation loss curves during a 100-epoch training period for U-Net

The training loss goes steadily down and eventually plateaus at something close to zero, which means that the model has minimised the error on the training set. The validation loss is initially decreasing with the training loss and then starts levelling off at around 20 epochs and staying consistent above the training loss. In other words, while the model keeps getting better and better on the training data, its performance on unseen validation data isn't changing anymore.

In the later stages, this gap between training and validation losses indicates mild overfitting. In spite of the prediction being good on the training set, it is not very good on the validation set. However, since the losses are not too far apart, overfitting is very low. The validation loss has already stabilised over the past few epochs and will probably not change much more with even a few more epochs, so it can be considered that the model converged.

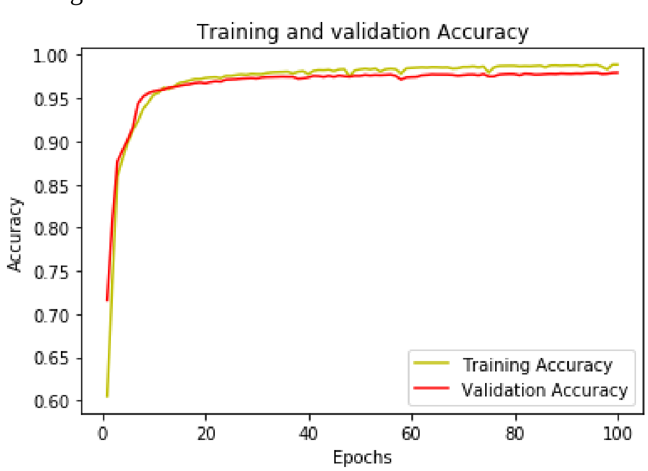

Fig. 4. Training and validation accuracy curves during a 100-epoch training period for U-Net

The Fig. 4, which shows training and validation accuracy over 100 epochs. The accuracy begins low (around 60%) very early in training as the model struggles to accurately classify the dataset's classes. Accuracy increases very fast during training, in the sense that the model is able to classify most of the data after the first 10 epochs of training. Their effective early learning and parameter adjustments are responsible for this sharp increase.

After this initial improvement, accuracy for both training and validation stabilises between 95% and 98%, with a minimum of about 20 epochs. The training and validation accuracy curves are close enough through training that the model seems to generalise well to new data without a lot of overfittings.

By the end of training, accuracy stops increasing past a value with very little variation, and this means that the model has reached a plateau. The consistently high accuracy across the two sets demonstrates the model's strong ability to classify different classes, including the classically challenging task of hotspot detection. Indeed, this stability and high performance ensure the robustness and reliability of the model.

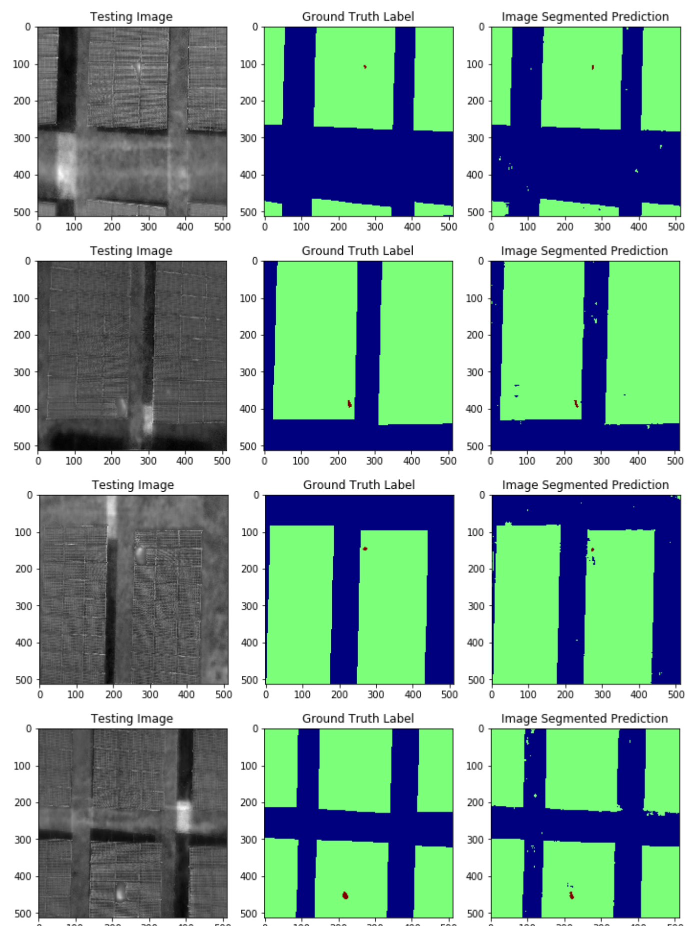

Fig. 5. The qualitative outcomes of the semantic segmentation predictions are class 1, background (blue), class 2, PV panels (green), and class 3, hotspots (red) using the U-Net architecture.

Figure 5 illustrates a qualitative assessment of the U-Net model's performance in segmenting thermal images of solar PV panels into three classes: hotspot (red), PV panel (green), and background (blue). A normalized thermal visualisation of the PV panel was generated for clearer interpretation. The leftmost image shows the original test image; the centre image presents the ground truth annotations, where each area is manually labelled—green for the PV panel, blue for background, and red for hotspots. The final image displays the U-Net model's segmented output, where each pixel is independently classified into one of the three specified categories.

Comparison of the ground truth and predicted segmentation shows that the model accurately captured the main regions of interest: PV panels and background. The predicted green and blue regions align closely with those in the ground truth, reflecting the model's strong capability in distinguishing PV panels from their surroundings.

For hotspot detection, the model successfully identified the hotspot region, though slight differences in shape and size compared to the ground truth can be observed. These minor discrepancies are likely due to the challenge of accurately detecting small and subtle hotspot features in thermal images. Nonetheless, the U-Net model effectively highlights these critical regions and captures essential features with high accuracy.

TABLE II . PERFORMANCE EVALUATION RESULTS FOR SEMANTIC SEGMENTATION OF MULTICLASS USING U-NET

No. of classes	IoU	mIoU	PA
Class 1: Background	0.9485		
Class 2: PV Panel	0.9677	0.7246	97.96%
Class 3: Hotspot	0.2578		

Overall, these findings confirm that U-Net is well-suited for multiclass thermal image segmentation of PV panels, effectively separating background, PV panels, and hotspots with minimal errors.

Table II summarises the quantitative performance of the U-Net model in segmenting the background, solar panel, and hotspot areas and highlights its strengths and areas for improvement in the segmentation accuracy. Overall, this study achieves a mean IoU of 0.7246 across all classes, which is a good result. The higher it is, the more the model's predictions overlapped with ground truth, the better it's performing.

The model attains high IoU scores of 0.9485 and 0.9677 for background (Class 1) and PV panels (Class 2), respectively, having high accuracy in segmenting those regions with close to perfect overlap to the ground truth.

Nevertheless, the IoU for hotspots (Class 3) is notably lower at 0.2578, which suggests that the precise identification of these tiny and subtle aspects in the thermal images is challenging. The lower score in this case is due to the difficulty to precisely detect and segment hotspots, which are often faint and small.

However, the model achieves an overall accuracy of 97.96% and a good pixel classification in the entire image. This high accuracy indicates that the model reliably classifies between background and PV panel regions and hence demonstrates general robustness to thermal image segmentation.

In order to contextualise these results, the model's performance was compared with other state-of-the-art methods in the field. For instance, L. Zhuang et al. [22] show that when used for solar panel segmentation, advanced deep learning methods can improve IoU scores by 34% through the use of their proposed cross-learning-driven U-Net method, which performs well on a range of datasets and typically results in an average IoU score of 74.017% (compared to the 40.017% benchmark). Furthermore, they showed robust performance on different datasets, achieving around 62% overall segmentation IoU. These models are very good at segmenting larger areas, such as solar panels, and that matches what this study found. In contrast, although the proposed model achieves background and solar panel segmentation performance as good as these leading methods, it has large gaps in hotspot detection. Furthermore, state-of-the-art models such as pyramid scene parsing network (PSPNet) [23] have been able to achieve competitive results in a number of segmentation tasks, but at the expense of demanding large annotated datasets, and hotspot detection is not incorporated in the same framework.

In this domain, the U-Net model achieves effective segmentation of large areas, including the background, solar panel regions and can recognise hotspot regions as well. Qualitative and quantitative evaluations confirm that the model correctly identifies these primary classes, suggesting the model as a potential reliable tool for automated solar panel segmentation on thermal images.

But the model struggles to pick up on smaller hotspots and segment them, which are crucial to identifying possible faults or inefficiencies in solar panels. It can recognise these regions but with low precision, especially with small and complex features. The inherent limitation in accurately segmenting minor regions out of a complex thermal image is pointed out.

While the model has overall strong general performance for classifying most of the pixels, the lower precision in hotspot detection indicates that there is a trade-off between overall accuracy and class specific performance. This implies that further refinement is necessary to make the model more effective in distinguishing between less frequent but important features.

This raises several areas for future research improvement. This large performance gap between segmenting hotspots shows that either additional strategies are required to improve the detection capabilities for small, subtle features or that more effort is needed to improve the performance of these methods. In addition, the high overall accuracy bears out the utility of the model on larger segments but makes one wonder to what extent the model can perform well on all classes under varying conditions. These limitations will be crucial for developing more effective monitoring and maintenance strategies for solar energy systems that allow better fault detection and better operational efficiency.

This study points to a first major limitation of the model in terms of its ability to properly segment hotspots. The low IoU of this class implies that the current U-Net configuration might not be optimal for the detection of small or less distinctive regions in thermal images. The reduced performance is also likely due to class imbalance in the dataset, as the number of background and solar panel regions is substantially higher than hotspots.

Future automated solar panel inspection using thermal imagery could include dataset augmentation, architectural change, and more advanced techniques. Such enhancements would be pivotal in developing more reliable and more effective systems for real-world applications.

V. CONCLUSION

In conclusion, this work shows that the U-Net deep learning model has great potential for effective multiclass semantic segmentation of solar panels and for hotspot detection. The effectiveness of the model in segmenting the solar panels and background regions suggests that the model is able to handle the complexity of the imagery from a PV system. Despite continued challenges with the smaller, less frequent hotspot class, results suggest that the proposed approach represents a promising means to improve the precision and consistency of fault detection in PV systems. The results highlight that deep learning models like U-Net can be beneficially applied to the real time monitoring and maintenance of PV systems through segmentation and analysis processes that lead to more proactive and efficient maintenance strategies. That in turn might prolong the operational life of solar installations and encourage sustainable energy production. In addition, the study points out further improvements in the area of hotspot detection. The relatively lower IoU for hotspots indicates that a refinement of the model is needed to better manage these critical but difficult features. Further work can be done to include other data sources, for example, multispectral imaging or advanced data augmentation, to handle class imbalance. Moreover, other gains in segmentation accuracy and robustness may be achieved by evaluating alternative deep learning architectures or ensemble methods. The U-Net model has performed well for solar panel segmentation and hotspot recognition, but more work is needed to overcome existing limitations and fully exploit deep learning for the renewable energy space.

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