Available online at
http://uppp.uitm.edu.my/online-issues.html

ESTEEM Academic Journal (EAJ)

e-ISSN: 2689-4934

ESTEEM Academic Journal Vol 20, September 2024, 77–90

Deep learning-driven thermal imaging hotspot detection in solar photovoltaic arrays using YOLOv10

Mohd Zulhamdy Ab Hamid[1*], Kamarulazhar Daud[1], Zainal Hisham Che Soh[1], Muhammad Khusairi Osman[1], Iza Sazanita Isa[1], Mohd Shawal Jadin[2]

[1]*Centre of Electrical Engineering Studies, Universiti Teknologi MARA, Cawangan Pulau Pinang, Permatang Pauh, Malaysia*
[2]*Faculty of Electrical and Electronics Engineering Technology, Universiti Malaysia Pahang Al-Sultan Abdullah, Pekan, Pahang, Malaysia*

ARTICLE INFO

Article history:
Received 30 June 2024
Revised 19 August 2024
Accepted 25 August 2024
Online first
Published 30 September 2024

Keywords:
Deep Learning
Thermal Imaging
Hotspot Detection
Solar PV Arrays
YOLOv10

DOI:
10.24191/esteem.v20iSeptember.1861.g1773

ABSTRACT

The effective management of solar photovoltaic (PV) arrays is vital to maximising energy generation and ensuring long-term performance reliability. The presence of faults, or partial shading, can give rise to hotspots in PV arrays, making their detection critical for timely maintenance and avoiding further impacts on their performance. This paper describes a new approach to the hotspot detection issue in thermal images of solar PV arrays by leveraging deep learning. This study employs the YOLOv10 (You Only Look Once, version 10) model to deliver very high accuracy and speed in identifying and localising hotspots under defined regions of interest (ROIs). The proposed method begins with taking thermal images from multiple solar PV installations while capturing a range of operational conditions and fault types. These images are annotated with hotspot regions to create a robust training dataset. Given YOLO's capability for real-time object detection with high precision and mean average precision (mAP), the YOLOv10 model is then implemented to train on this dataset. Multiple changes were made to the YOLOv10 hyperparameters to optimise them for detecting hotspots in thermal images. The experimental scenario of this paper demonstrates that this approach indeed performs significantly better than standard image processing methods as well as prior deep learning models for detecting both hotspot accuracy as well as speed of processing the images. The YOLOv10 method demonstrated the highest available classification performance with a mAP at intersection over union (IoU) of 0.5 accuracy of 0.91 with inference time suitable for real-time applications. The sample results demonstrated the model's continuous ability to detect hotspots and provide location data under various conditions, such as crossing through different times of day and weather. The results of this study demonstrate that YOLOv10 can be

[1*] Corresponding author. *E-mail address: 2023504807@isiswa.uitm.edu.my*
https://doi.org/10.24191/esteem.v20iSeptember.1861.g1773

used for improved detection of hotspots in the explicably thermal imagery of solar PV arrays.

1. INTRODUCTION

The current human society embraces the use of solar PV arrays as a renewable energy system, which means that proper maintenance techniques are required to enhance the durability of the system. Solar PV arrays are susceptible to diverse problems, including partial shading, cell degradation, and debris buildup, which results in hotspot formation [1]. Moreover, these hotspots not only reduce the efficiency and maximum power of the affected panels but can also progress to the formation of extensive damages, which would have negative impacts on both the efficiency and longevity of the general PV system [2]. Therefore, it is important to identify the hotspots as soon as possible and determine their exact location to be able to decide on performing maintenance and preventing possible risks on time.

Previous approaches to detecting hotspots often require manual visualisation in conjunction with only a basic thermal imager, which may be laborious and error-prone work [3]. Recent deep learning advancements, especially object detection-related research, have provided a possible solution for this problem. Of all the currently available models, the series of YOLO has obtained quite compelling attention since it is able to perform real-time object detection with high accuracy. A later version is YOLOv10 [4], which has been enhanced with a number of features that have made it especially suitable for challenging tasks, especially in diverse and dynamic backgrounds like thermal images of solar photovoltaic arrays.

This research aims to investigate the benefits of using YOLOv10 for detecting hotspot regions of interest in thermal images of solar power plants. So, using an improved version of YOLOv10 at the same time would be efficient and effective for following schemes of hotspot detection to help maintain solar PV systems and improve their efficiency. The scope of this paper is thus to fine-tune a pre-trained YOLOv10 model for thermal hotspot detection, with an eventual view of real-time monitoring and control of solar photovoltaic arrays. This work tries to confirm the efficacy of this approach and show its importance and relevance to renewable energy.

2. LITERATURE REVIEW

The detection of hotspots in solar PV arrays has attracted a lot of research interest because of the importance of minimising hotspot-related degradation of solar system performance and its potential damaging effects. Conventional approaches to identifying hotspots are simplistic, such as through visual surveys or rudimentary infrared scans [3]. Conventional inspection techniques, despite their effectiveness, are escorted by high costs in terms of time, produce, and, most importantly, can be compared with human errors in some cases [5]. While basic thermal imaging methods are able to detect temperature variations, which in turn is indicative of an object's temperature, their resolution may not be sufficient to pinpoint areas of the object that are emitting high levels of temperatures and segregate between different types of hotspots [6]. Several studies that use image processing techniques for thermal images using thresholding and edge detection techniques have been reported in the literature, and these approaches have been noted to suffer from fluctuations in environmental conditions and the non-uniformity of PV array surfaces.

The combination of concepts of machine learning and deep learning in the last few years has given new dimensions to the hotspot detecting field. Typically, various features were used in the early adoption of machine learning techniques combined with the classification algorithms such as support vector machines (SVMs), decision trees, and so on [7-8]. Though these methods increased the chances of detecting abnormalities, these techniques were hard-coded and demanded feature engineering and have shown poor

https://doi.org/10.24191/esteem.v20iSeptember.1861.g1773

results when generalised to different types of PV arrays and environments. The use of the convolutional neural network (CNN) introduced a significant improvement in end-to-end learning and higher accuracy for image-based tasks [9]. Different architectures of CNNs have been used for hotspot detection, with significant enhancements in comparison with the conventional techniques [10].

In a 2022 study conducted by F. Fan et al. [11], the dataset was split into two distinct parts: an unenhanced set containing 39 images with hotspots and 39 images without, and an enhanced set comprising 292 hotspot images and 192 non-hotspot images. The researchers employed a five-layer CNN architecture to detect and classify infrared near-field images of photovoltaic (PV) modules. The accuracy results showed that the CNN model outperformed the Naïve Bayes classifier in both datasets, achieving 89.47% accuracy on the unenhanced dataset (compared to Naïve Bayes' 79.49%) and an impressive 96.58% accuracy on the enhanced dataset (compared to Naïve Bayes' 91.78%). The performance improvement in the enhanced dataset was particularly significant.

In a 2023 study by H. Bakir [12], a convolutional neural network (CNN) was employed to extract features from thermal images of both operational and faulty photovoltaic (PV) modules. The extracted features were then validated using a Long Short-Term Memory (LSTM) model, with training and validation conducted across varying image quantities. The dataset was divided into three scenarios: Case 1 with 300 images, Case 2 with 500 images, and Case 3 with 1,000 images. When using raw data, the LSTM model achieved an accuracy of 80.99%, outperforming the CNN's accuracy of 73.55%. However, when data augmentation was applied, the CNN demonstrated significant improvements, achieving accuracies of 87.84%, 86.42%, and 95.05% across the three cases, respectively, while the LSTM model's accuracies were 70.16%, 77.82%, and 78.39%. The results indicate that while LSTM excelled with raw data, CNN's performance was markedly enhanced with data augmentation.

The family of models YOLO was developed as an answer to the real-time object recognition tasks with a high degree of accuracy. Proposed by [4], the YOLO model re-imagined object detection as a single regression task, wherein bounding boxes together with class probabilities were directly predicted from the full image in a single pass. This approach significantly cut the computation time as opposed to those methods that call for sequential passes over the image. In YOLOv3, there were enhancements made in accuracy and detection of multiple scales, making it more versatile [13]. With regard to the developments in network architecture, training methods, and post-processing steps, YOLOv5 improved performance once again [14-15]. The latest of them is YOLOv10, which has been developed based on the state of the art in deep learning and computer vision [4]. It has a more complex framework for feature extraction, including the backbone network, improved anchor box mechanisms for better localisation, and improved loss functions for training purposes. We also observed that the real-time processing nature of YOLOv10 in combination with a relatively high detection accuracy makes it ideally suited for tasks where fast detection and proper identification of small or tightly situated objects is necessary, such as detection of hotspots in thermal images of solar PV arrays.

These advancements of YOLO models, including YOLOv10, are applied in the present hotspot detection while eliminating the drawbacks of previous methods. Through the same approach that the current YOLOv10 offers a model that can learn from thermal images with annotations, YOLOv10 offers a reliable and efficient means of hotspot identification [16-17]. This not only increases the dependability of PV array maintenance but also increases renewable energy use by boosting output and minimising interruptions.

3. METHODOLOGY

To implement an efficient and accurate detection algorithm for hotspot ROIs in thermal images of solar PV arrays, this study proposed a deep learning-based approach that used the YOLOv10 model. The methodology, as illustrated in Fig. 1, encompasses the following: Collection and annotation of thermal

https://doi.org/10.24191/esteem.v20iSeptember.1861.g1773

image datasets. The data are so imperative that they are meant for both training and testing the YOLOv10 model. Images are captured in such a way that PV systems can cover large areas that fix working conditions and fault types, which boosts the reliability of the model. After the dataset was acquired, in the annotation phase, the specific hotspot areas are labelled systematically towards the development of a ground truth. Thus, this stage becomes so important for enabling the development of a hot spot feature learning in YOLOv10. This is followed by tuning the configurations towards further refinement of the YOLOv10 model for thermal hotspot detection. Possibly, things to be changed are all the following: dimension of the input of the network, learning rate, and other hyperparameters that may give better output in the context of this application.

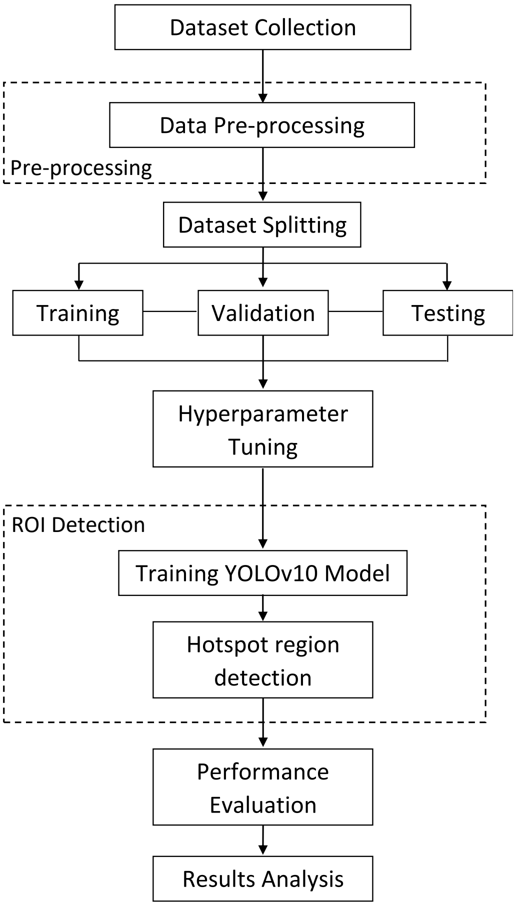

Fig. 1. Methodology flowchart of study implementation

The training phase consists of passing the annotated dataset into the YOLOv10 model. In this process, preprocessing techniques are used to improve the comprehensiveness of the proposed model. These techniques aid the model to handle variations in thermal images, such as in terms of lighting, angle, and environmental impacts. The training is done by using cross entropy for classification and mean squared error for localisation so as to accurately detect and localise the hotspots. After the training of the model is complete, the model is then tested by a validation and test set. Evaluation is done using performance indicators like precision, recall, and mean average precision (mAP). Furthermore, the time taken for inference is evaluated to identify if the model can support real-time use. We demonstrate that by using the

https://doi.org/10.24191/esteem.v20iSeptember.1861.g1773

YOLOv10-based approach, it is possible to achieve significant improvements after results analysis with baseline methods. The last one is the necessary utilisation of the trained model in practical activities and materials. This is in addition to incorporating thermal imaging in the model to facilitate monitoring of the PV arrays on a continuous basis. As a result of the methodology, the developed system can accurately identify potential hotspots instantaneously and therefore enable timely resolution of the issue, with a beneficial impact on the general power output of solar PV systems.

3.1 Dataset Collection

In obtaining the thermal images for this research, a systematic method was followed in order to obtain a large dataset with sampling characteristics that encompass a wide range of various conditions of operation in solar PV arrays. Photographs were taken by high-performance thermal cameras on drones and mobile platforms that allowed to image large-scale PV plants from above 30 meters in height. The data was collected within different times in a day, different weather conditions, and different seasons so as to encompass a broad thermal signature of normal and abnormal performance. To further strengthen this study, images were captured from the solar PV farms in Kelantan, Malaysia with different types of panels and settings. This led to data collection that entailed over 888 images with 390 raw thermal images labelled with hotspots, where each image has been annotated to point to the areas with hotspots. This rich and diverse dataset excellently complements this work since it offers the model a broad range of data variations on which it will be trained, thus helping the YOLOv10 model generalise well in different PV array settings and conditions.

3.2 Data Annotation

The data annotation for this study entailed a careful and detailed labelling of hotspot areas in thermal images obtained for the formation of a high-quality training dataset for the YOLOv10 model. First, thermal images were used in a specialised annotation tool, namely LabelImg, that is intended for accurate labelling [18]. Expert annotators involved in bracketing a high number of images in detecting hotspots in solar PV arrays usually analyse every image in order to look for hotspots that are defined by highly contrasting temperatures, which could mean faults or inefficiency. The definition of each hotspot area was done with much precision by the use of bounding boxes, which helped to minimise the chances of mislocalisation. In addition, the annotations provided include classification labels to categorise all different regions of hotspots, likely caused by partial shading, cell damage, or even debris buildup [1]. This enormous annotation was really necessary to effectively train the YOLOv10 model for identifying hotspot regions, differentiating those across a variety of thermal imaging conditions. The annotated dataset described above was comparatively analysed with the database to ensure the correct organisation of all entries. Any missing information or discrepancies found were corrected by thorough validation to ensure the training data compiled was complete and accurate.

Bounding Box Equation for YOLO Annotation

In YOLO annotation, each bounding box is defined by five key parameters: class id, (x), (y), (w), and (h). These parameters are normalised to the image dimensions and represent the center coordinates, width, and height of the bounding box. Here's how they are calculated:

(i) Class ID represents the number of class names annotated for the bounding box region of interest of the images.

(ii) (x), Eq. (1) and (y), Eq.(2) represent the coordinates of the center of the bounding box, normalised by the width and height of the image respectively [4], [19].

(iii) (w), Eq (3) and (h), Eq.(4) denote the width and height of the bounding box, also normalised by the width and height of the image [4], [19].

https://doi.org/10.24191/esteem.v20iSeptember.1861.g1773

The equations for these parameters are as follows:

$$x = \frac{x_{\min} + x_{\max}}{2W} \tag{1}$$

$$y = \frac{y_{\min} + y_{\max}}{2H} \tag{2}$$

Here, $x_{\min}$ and $x_{\max}$ are the minimum and maximum x-coordinates of the bounding box, $y_{\min}$ and $y_{\max}$ are the minimum and maximum y-coordinates, and W and H are the width and height of the image [4], [19].

$$w = \frac{x_{\max} + x_{\min}}{W} \tag{3}$$

$$h = \frac{y_{\max} + y_{\min}}{H} \tag{4}$$

Where; w calculates the width of the bounding box as a fraction of the image width and h calculates the height of the bounding box as a fraction of the image height.

Thus, the YOLO annotation for the bounding box would be represented as Fig. 2 below in .txt file format. These normalised values enable the model to accurately detect and localise objects in different images, regardless of their original dimensions.

```
File    Edit    View

1 0.4412393162393162 0.37897302350427353 0.05074786324786329 0.17528044871794873
```

Fig. 2. Bounding box labels for YOLO in .txt, [class id, x_center, y_center, width, height]

3.3 Training Process

In order to achieve high accuracy and efficiency, the YOLOv10 model training process for detecting hotspots in thermal images of solar PV arrays involved several key steps. First, this study implemented data preprocessing so that the input quality would be constant while working with thermal images. This involved scaling images to fit the input dimensions required by the model and standardising pixel values, which improved upon the feature extraction methods used. As shown in Table 1, hyperparameter tuning was done using the grid search method that identifies the best learning rate, batch size, and momentum, therefore facilitating stable and effective training. During the grid search method used in this study, different combinations of hyperparameters were tested, including learning rates such as 0.001, 0.005, and 0.01, batch sizes (1, 2, 4, 8) as well as momentum values like 0.8, 0.9, and 0.95.

For each hyperparameter, this study selected a predefined range of possible values and tested them all together. With each combination, the model underwent a full training cycle. The final model configuration was selected based on the set of hyperparameters that gave the best performance, as measured by stability during training and high accuracy in hotspot detection. Training was done in a high-performance computing

https://doi.org/10.24191/esteem.v20iSeptember.1861.g1773

environment using an NVIDIA GeForce RTX 3050 Laptop GPU with 4096MiB and was done using PyTorch for the development of the model. The model was iteratively trained, validated, and tested against continuous monitoring over multiple epochs to avoid overfitting and ensure that the model has converged. The consequence is that heavy training of YOLOv10 allowed it to learn intensive features of complex patterns of thermal hotspots, thus providing a real-life reliable detection system in PV array applications.

Table 1. Hyperparameter tuning for training process

Hyperparameter/Configuration	Description
Input image	[640, 512]
No. of class	1 (hotspot)
Optimizer	SGD
Learning rate	0.01
Batch size	8
Total of epoch	200
Dataset split	80% (training) : 10% (validation) : 10% (test)

3.4 Performance Evaluation Metrics

Mean Average Precision (mAP)

The mean Average Precision (mAP) as depicted in Eq. (5), is a vital metric for assessing the model's proficiency in accurately detecting hotspots in solar photovoltaic (PV) panels [20]. This metric evaluates the precision and recall of the predicted hotspots against actual hotspots over various confidence thresholds. By determining precision and recall at different confidence levels, mAP offers a comprehensive measure of the model's overall performance. A higher mAP signifies better hotspot identification across all categories, indicating the model's effectiveness in differentiating between true hotspots and false positives.

$$mAP = \frac{1}{|\mathrm{TP}|+|\mathrm{FP}|} \sum_{i=1}^{N} Precision(i) \ x \ Recall(i) \tag{5}$$

Precision and Recall

Precision and recall are critical metrics for evaluating the model’s performance in hotspot detection [20]. Precision, as shown in Eq. (6), assesses the proportion of accurately identified hotspots out of all predicted hotspots, thereby providing insight into the reduction of false positives. Conversely, recall, illustrated in Eq. (7), evaluates the proportion of actual hotspots that the model successfully detects, highlighting the reduction of false negatives. Combined, these metrics offer a thorough assessment of the model's accuracy and dependability in identifying hotspots within solar PV panels.

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

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

https://doi.org/10.24191/esteem.v20iSeptember.1861.g1773

Where; TP is the total number of true positive instances, FP is the total number of false positive instances, TN is the total number of true negative instances, FN is the total number of false negative instances, N is the total number of hotspot predictions, *Precision(i)* is the *i*th prediction, and *Recall(i)* is the *i*th prediction.

4. RESULTS AND DISCUSSION

The learning effectiveness and detection precision clarity that both training and performance metrics, as proposed and reported by the YOLOv10 model, respectively, put into use in the development process of detecting thermal image hotspots of solar photovoltaic arrays are revealing. Time series plots reflected in Fig. 3 disclose persistent improvement regarding several important metrics, which gives an indicator of a model that is so learnt in the easy task of learning and generalising hotspot detection. The train/box_om graph is plotted, and from the graph, the bounding box regression loss gradually falls during the complete training period from high values to convergence in time. In some sense, this might be interpreted to mean that model predictions on the location and size of bounding boxes around detected objects have graduated towards true values with time. In the cls_om, it has a very strong decrease in the graph of general classification loss and indicates an enhancement in the model's skill about the proper identification of hotspots derived from the thermal images. Again, the distribution of the focal loss within the trains/dfl_om graph also performs this type of process, showing downward trends and indicating that focus is moving onto harder examples with raised overall detection skill.

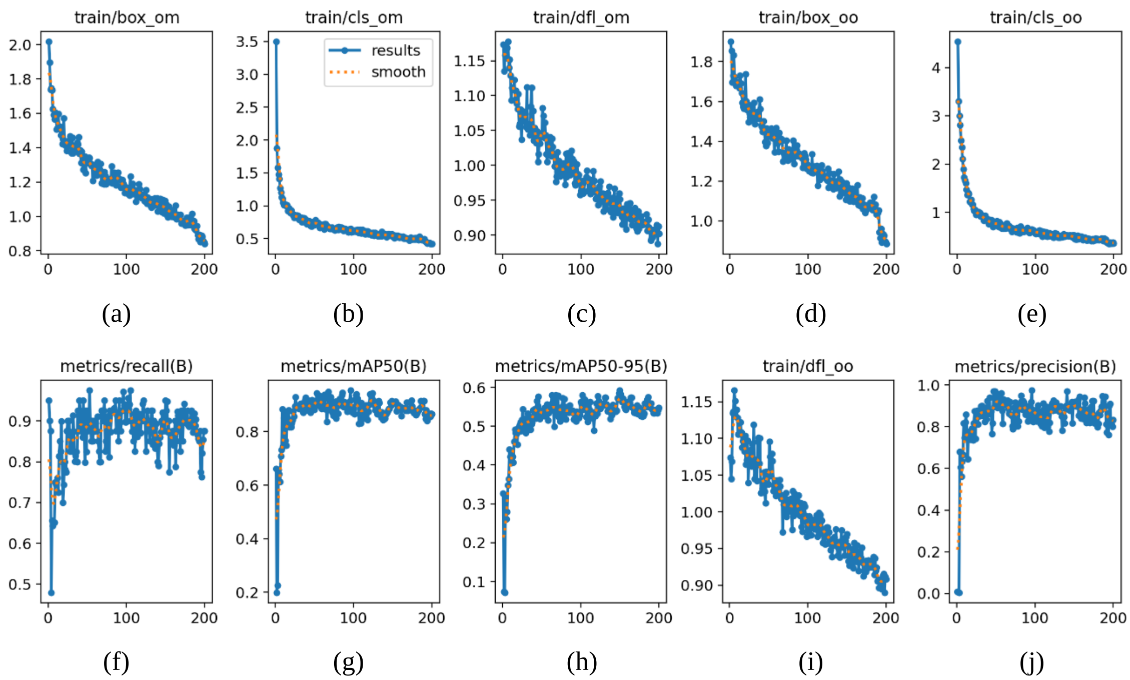

Fig. 3. Graphical view of training and validation process and evaluation performance metric over 200 epochs; (a) bounding box regression loss; (b) classification loss; (c) distribution focal loss; (d) validation of bounding box regression loss; (e) validation of classification loss; (f) Recall; (g) mean Average Precision at a 50% Intersection over Union (IoU) threshold; (h) mean Average Precision across multiple IoU thresholds (from 50% to 95%); (i) validation of distribution focal loss; and (j) Precision

https://doi.org/10.24191/esteem.v20iSeptember.1861.g1773

Other graphs, such as train/box_oo, train/cls_oo, and train/dfl_oo, add further evidence supporting the learning pattern of this model in different dimensions or stages of training, where one can continuously notice the decreases of the values of losses. All these put together give evidence that this model is working fine in fine-tuning its parameters towards optimisation in detection precision and robustness. The evaluation metrics give a more global view of the model's performance. There is a very high recall, peaking at around 0.9 on the metrics/recall (B) graph, implying the model has very high sensitivity and can capture almost all true hotspots from thermal images. In this regard, the graph metric/mAP50(B) shows the mean Average Precision at 50% intersection-over-union. There is an increasing curve that becomes stable to a point of about 0.8. This indicates both the precision and recall of the model and hence confirms that it correctly detects the hotspots and places them, baring extensive overlap with the ground truth.

This would be further asserted by the metrics/mAP50-95(B) plot, taking into account mean Average Precision across several IoU thresholds, from 50% to 95%, and maintaining performance at a good level for different detection criteria, with a final value around 0.6. This full metric will have the model not only be very precise under normal conditions but also resistant in cases of strict localisation requirements. To be precise, the graph of metrics/B shows an augmentation and then a slight stability around 0.8, indicating that at this value, the model performs optimal minimisation of false positives while maintaining a high level of correct detections.

After 200 epochs in around 0.359 h, the optimizer was stripped from keyed-up weights of the YOLOv10 model to reduce file size to 5.7 MB. For final validation, best model weights were done on setup running Ultralytics with Python 3.9.19 and PyTorch 2.3.1 compiled on NVIDIA GeForce RTX 3050 Laptop GPU system. The fused YOLOv10n model comes with 285 layers with 2,695,196 parameters that achieve 8.2 GFLOPs. The model was trained over 710 images and validated on 89 images containing hotspot instances, achieving a precision (P) of 0.92, recall (R) of 0.95, mean average precision at IoU 0.5 (mAP50) of 0.91, and mean average precision at IoU 0.5 to 0.95 (mAP50-95) of 0.592. 0.3 ms in preprocessing, 5.6 ms in inference, and 0.3 ms in post-processing per image—underscoring the need to have both efficient and correct detection of hotspots in thermal images of photovoltaic solar arrays. The performance results obtained are tabulated in Table 2 below.

Table 2. Performance evaluation for training and validation over 200 epochs

Evaluation Metrics	**Reading Results (%)**
precision (P)	92.00%
recall (R)	95.00%
mAP50	91.00%
mAP50-95t	59.20%

The curve represents how the YOLOv10 model performs in the hotspot detection within thermal images by relating its precision-recall. Fig. 4 explains the curve in which the model possesses a precision value of 0.91 under different recall requirements. Thus, the model can predict hotspots precisely to a high degree of truth and maintain low false positives. The sharp rise into a peak value on the right-hand side of the curve indicates that the model correctly identified most of the positives. After this point, the precision starts falling. That means the model is working; it can pick most of the possible hot spots with high confidence. As a result, the calculated mAP at the threshold value of IoU equal to 0.5 is equal to 0.91 for all entries and creates the sound base of lidar rigour and reliability in models identifying hotspots. Overall complete findings, with the right calibration, suggest that this model can make assignments with a fairly balanced trade-off between precision and recall.

https://doi.org/10.24191/esteem.v20iSeptember.1861.g1773

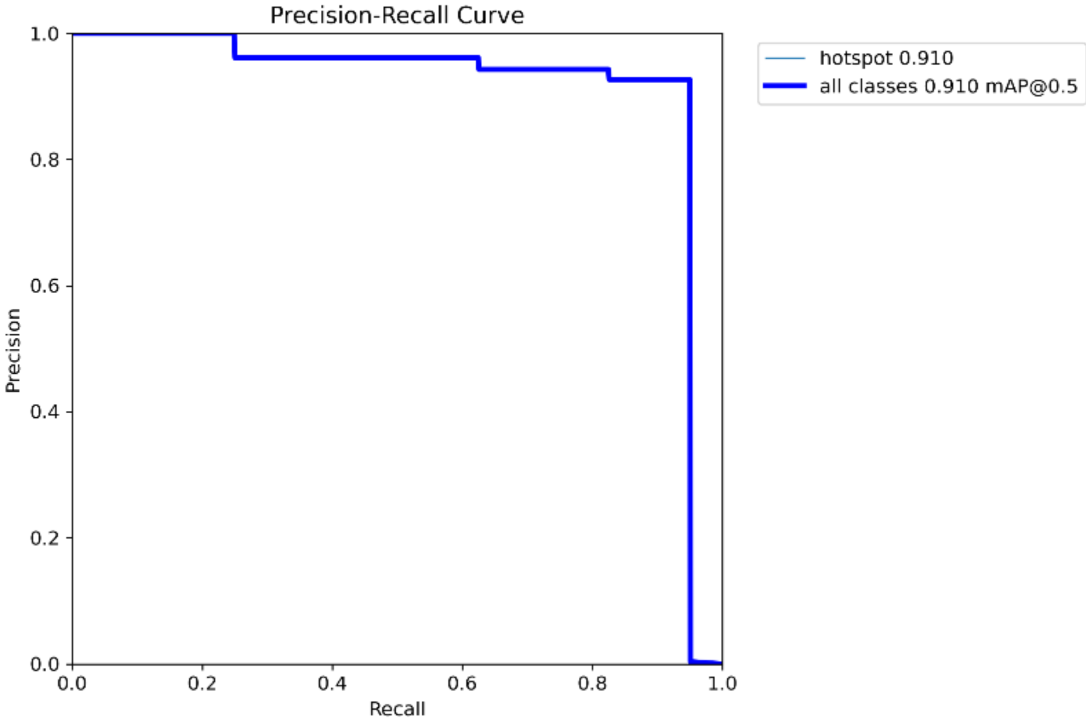

Fig. 4. Plotting graph of Precision-Recall Curve

In other words, the integration of the decreasing loss metric and high stable evaluation metric, such as recall, precision, and mAP values, at the end of a training epoch indicated the possibility to train and optimise the YOLOv10 model properly for hotspot detection in thermal images. The high recall and high precision of the model validator ensure that the identification and localisation of hotspots are valid. Therefore, this tool is important in the maintenance and re-establishment of the solar photovoltaic facilities' effective operation. With that, the capability of the fault detected is extremely needed in order to detect and mitigate faults, hence boosting operational performance of solar energy systems in time [21].

Qualitative results, as shown in Fig. 5, through the validation and testing depicted from the provided thermal images, show the extensive performance of the YOLOv10 model in both identification and localising hotspots in solar PV arrays or modules. The raw thermal fusion image created from the thermal camera with temperature readings better locates hotspots compared to the total dependency of the hot colour mapping. This change helps to maintain accurate colour representation and evade the deceitful yellowish tint while providing a better means of visually distinguishing hotspots.

With each hotspot, the image is annotated wherever there is identification, along with a confidence score, indicating that the model finds the regions of interest correctly. The fact that hotspots tend to be consistently identified under different imaging conditions clearly points to a high generalisation capability of the model. Such confidence scores, mainly from 0.6 to 0.9, signify the dependability of the model in its predicted outcomes. In images that contain multiple hotspots, it has detected and localised all the points, portraying the ability to handle complicated scenes. The bounding boxes that distinctly outline the hotspots show the effectiveness of the YOLOv10 implementation towards the provision of perfect localisation. The fact that such qualitative results are consistent with the quantitative metrics obtained during the training process leads to agreement on the suitability of the model for real-world applications in monitoring and

https://doi.org/10.24191/esteem.v20iSeptember.1861.g1773

performance improvement in solar PV arrays. Another notion of justification for visual consistency with high detection confidence is model robustness and accuracy related to thermal anomaly detection, important for timely maintenance interventions.

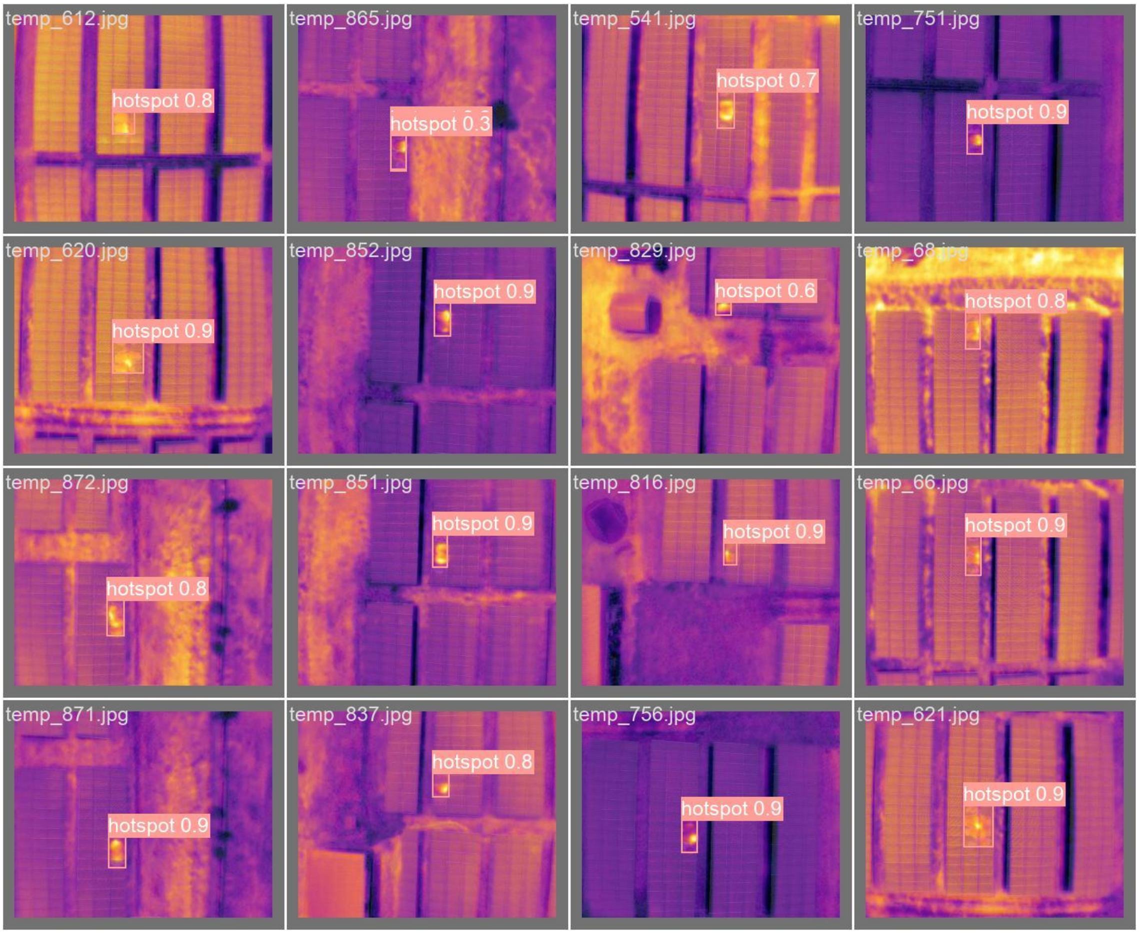

Fig. 5. Qualitative result of validation and testing visualization for thermal images dataset of solar PV arrays

The improved the feature of the YOLOv10 model in solar PV arrays to detect hotspots has a huge impact on maintenance and operational efficiency associated with solar power systems. The more precise detection of hotspots makes it possible to take preventive action in time and thus avoid any possible damages and, consequently, prevent the chances of severe faults that could throttle the production of electrical energy. As the first step in dealing with these thermal anomalies, the maintenance crew conducts the most partial repair strategies, which consequently prolong the functional lifespan and optimise the performance of the system. In addition, this leads to more production of energy and higher returns on investments. Furthermore, if a high-tech detection system is put in place, the concurrent losses due to rooftop downtime and maintenance will drastically diminish, providing the solar power unit with a path to being successful and sustainable.

Despite such promising results, several limitations were encountered during the course of this experiment. As the quality of thermal images fluctuates broadly because of weather conditions, time of day,

https://doi.org/10.24191/esteem.v20iSeptember.1861.g1773

or different camera specifications, accuracy in detection becomes difficult to maintain. Cloud conditions, other general environmental conditions, or dust deposited on panels may mask the hotspots and give negative false or reduced precision in hotspot detection [5]. Moreover, the dataset used for training the model was limited in diversity, which might affect the generalisability of the model to different PV array configurations or geographic locations. These factors highlight the need for a more robust dataset and further refinement of the model to handle diverse conditions effectively [22].

Future studies can focus on various paths for further enhancement of the present methodology. Firstly, increasing the dataset to a wider range of thermal images taken under different environmental conditions will increase the robustness and applicability of the model. The use of advanced image processing to reduce variability in image quality may help further improve detection accuracy. Furthermore, the research on how YOLOv10 can be combined with other deep learning models, such as CNNs, which are tailored to extract specific image features, may lead to some synergistic benefits in detecting hotspots [17][9][10]. Other than hotspot detection, future studies can apply this framework to the detection of different fault types in PV arrays, like microcracks or delamination, which will extend the scope and versatility of the system. Finally, actual implementation of the model in the real-time monitoring framework and evaluation of its efficiency in live conditions would mean a lot regarding its practical usefulness and reliability in real-life applications.

5. CONCLUSION

In conclusion, this study demonstrates the efficiency of the YOLOv10 model in hotspot detection from thermal images of solar PV arrays, considering the evident enhancement in accuracy and efficiency. This investigation very clearly pointed out that early detection of hotspots is crucial in keeping a solar photovoltaic system in optimal performance without energy losses and not damaging the system's hardware. By leveraging the architecture of YOLOv10, quite impressive recall and precision have been achieved. It actually means that the model gives a good result even if minor anomalies are detected on the thermal images. The core lies in the diversity of the carefully curated and annotated datasets that practice making the model detect multiple patterns of hotspots under real-world circumstances. Another big thing the study accomplished was that it could fine-tune YOLOv10 for thermal imaging tasks, until now having some complications in most tasks regarding quality and image differences in different ambient conditions. The model's evaluation metrics are at mAP50 of 0.91, while at mAP50-95, it is 0.592-further underpin the ability to offer good accuracy and reliability in the detection much needed for proactive maintenance strategies in solar PV systems. This training procedure, associated with extensive data preprocessing and hyperparameter optimisation, greatly improved model generalisation capability, hence widening its operational scope with regard to a good number of operational scenarios. This kind of advanced detection of hotspots is very helpful to solar power industry practitioners. Higher accuracy with regard to hotspot detection should improve the system reliability of the solar power plant, thereby economising on maintenance costs and maximising power generation. What is supported apart from the quick inference capability of YOLOv10 is the in-time observation features. These can prompt issue-driven investigations. Perhaps other scholars may get inspired by their permissions, which expand the possibility for a number of further research directions. Increasing the dataset with more types of images will significantly improve the robustness of the model. More general fault detection may approach further accuracy with the integration of more sensor information and the application of ensemble learning methods. Applications of the technique will become widespread and include monitoring wind turbines, assessing grid infrastructure, and many other applications across all areas of renewable energy industries. This thus reveals that there exists a great potential for deep learning-based transformation towards augmenting ongoing maintenance and operational efficiencies within solar photovoltaic arrays to further develop more rational alternatives for sustainable energy.

https://doi.org/10.24191/esteem.v20iSeptember.1861.g1773

6. ACKNOWLEDGEMENTS/FUNDING

The authors express their deepest gratitude to Universiti Teknologi MARA (UiTM) and the Centre for Electrical Engineering Studies at UiTM Penang Branch for the invaluable support and financial sponsorship provided towards this research.

7. CONFLICT OF INTEREST STATEMENT

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

8. AUTHORS' CONTRIBUTIONS

Mohd Zulhamdy Ab Hamid: Conceptualisation, methodology, formal analysis, investigation and writing-original draft; **Kamarulazhar Daud**: Conceptualisation, supervision, writing- review and editing, and validation; **Zainal Hisham Che Soh**: Conceptualisation, methodology, and formal analysis; **Mohd Shawal Jadin**: Conceptualisation, formal analysis, and validation; **Iza Sazanita Isa**: Conceptualisation, formal analysis, and validation; **Muhammad Khusairi Osman**: Conceptualisation and validation.

9. REFERENCES

[1] P. Bharadwaj, K. Karnataki, and V. John, "Formation of Hotspots on Healthy PV Modules and Their Effect on Output Performance," in *2018 IEEE 7th World Conference on Photovoltaic Energy Conversion (WCPEC) (A Joint Conference of 45th IEEE PVSC, 28th PVSEC & 34th EU PVSEC),* pp. 0676–0680, Jun. 2018. Available: doi: 10.1109/PVSC.2018.8548126.

[2] S. Deng et al., "Research on hot spot risk for high-efficiency solar module," in *Energy Procedia, Elsevier Ltd,* pp. 77–86, 2017. Available: doi: 10.1016/j.egypro.2017.09.399.

[3] Y. Zefri, A. Elkettani, I. Sebari, and S. A. Lamallam, "Thermal infrared and visual inspection of photovoltaic installations by uav photogrammetry—application case: Morocco," *Drones,* vol. 2, no. 4, pp. 1–24, Dec. 2018. Available: doi: 10.3390/drones2040041.

[4] A. Wang et al., *YOLOv10: Real-Time End-to-End Object Detection,* May 2024, [Online]. Available: http://arxiv.org/abs/2405.14458

[5] U. Pruthviraj, Y. Kashyap, E. Baxevanaki, and P. Kosmopoulos, "Solar Photovoltaic Hotspot Inspection Using Unmanned Aerial Vehicle Thermal Images at a Solar Field in South India," *Remote Sens (Basel),* vol. 15, no. 7, Apr. 2023. Available: doi: 10.3390/rs15071914.

[6] O. E. Ikejiofor, Y. E. Asuamah, H. O. Njoku, and S. O. Enibe, "Detection of Hotspots and Performance Deteriotations in PV Modules under Partial Shading Conditions Using Infrared Thermography †," *Engineering Proceedings,* vol. 2, no. 1, 2020. Available: doi: 10.3390/ecsa-7-08201.

[7] J. Starzyński, P. Zawadzki, and D. Harańczyk, "Machine Learning in Solar Plants Inspection Automation," *Energies (Basel),* vol. 15, no. 16, Aug. 2022. Available: doi: 10.3390/en15165966.

[8] K. Nitturkar, S. Vitole, M. Jadhav, and V. G. Sridhar, "Solar Panel Fault Detection Using Machine Vision and Image Processing Technique," in *2023 International Conference on Next Generation Electronics, NEleX 2023, Institute of Electrical and Electronics Engineers Inc.,* 2023. Available: doi: 10.1109/NEleX59773.2023.10421272.

[9] Ihtyaz Kader Tasawar, Abyaz Kader Tanzeem, Md. Mosaddequr Rahman, Tahmid Ahmed, Mohaimenul Islam, and Shah Faiza Zarin, "Fault Diagnosis of PV Modules Using Deep CNN,"

in *2022 International Conference on Energy and Power Engineering (ICEPE),* pp. 1–6, 2022. Available: doi: 10.1109/ICEPE56629.2022.10044899.

[10] M. Vlaminck, R. Heidbuchel, W. Philips, and H. Luong, "Region-Based CNN for Anomaly Detection in PV Power Plants Using Aerial Imagery," *Sensors,* vol. 22, no. 3, Feb. 2022. Available: doi: 10.3390/s22031244.

[11] F. Fan, Z. X. Na, C. Z. Zhang, H. R. Li, and C. L. Tong, "Hot Spot Detection of Photovoltaic Module Infrared Near-field Image based on Convolutional Neural Network," in *Journal of Physics: Conference Series, Institute of Physics,* 2022. Available: doi: 10.1088/1742-6596/2310/1/012076.

[12] H. Bakır, F. A. Kuzhippallil, and A. Merabet, "Automatic detection of deteriorated photovoltaic modules using IRT images and deep learning (CNN, LSTM) strategies," *Eng Fail Anal,* vol. 146, Apr. 2023. Available: doi: 10.1016/j.engfailanal.2023.107132.

[13] A. Di Tommaso, A. Betti, G. Fontanelli, and B. Michelozzi, *A Multi-Stage model based on YOLOv3 for defect detection in PV panels based on IR and Visible Imaging by Unmanned Aerial Vehicle,* Nov. 2021, [Online]. Available: http://arxiv.org/abs/2111.11709

[14] T. Sun, H. Xing, S. Cao, Y. Zhang, S. Fan, and P. Liu, "A novel detection method for hot spots of photovoltaic (PV) panels using improved anchors and prediction heads of YOLOv5 network," *Energy Reports,* vol. 8, pp. 1219–1229, Nov. 2022. Available: doi: 10.1016/j.egyr.2022.08.130.

[15] T. Sun, H. Xing, S. Cao, Y. Zhang, S. Fan, and P. Liu, "A novel detection method for hot spots of photovoltaic (PV) panels using improved anchors and prediction heads of YOLOv5 network," *Energy Reports,* vol. 8, pp. 1219–1229, Nov. 2022. Available: doi: 10.1016/j.egyr.2022.08.130.

[16] J. Wang et al., "Deep-Learning-Based Automatic Detection of Photovoltaic Cell Defects in Electroluminescence Images," *Sensors,* vol. 23, no. 1, Jan. 2023, doi: 10.3390/s23010297.

[17] Y. Li, S. Chen, T. Rapakoulia, H. Kuwahara, K. Y. Yip, and X. Gao, "Deep learning identifies and quantifies recombination hotspot determinants," *Bioinformatics,* vol. 38, no. 10, pp. 2683–2691, May 2022. Available: doi: 10.1093/bioinformatics/btac234.

[18] Tzutalin, *LabelImg,* 2015, Free Software: MIT License. Accessed: Jul. 02, 2024. [Online]. Available: https://github.com/tzutalin/labelImg

[19] C.-Y. Wang, I.-H. Yeh, and H.-Y. M. Liao, *YOLOv9: Learning What You Want to Learn Using Programmable Gradient Information,* Feb. 2024, Accessed: Jun. 05, 2024. [Online]. Available: http://arxiv.org/abs/2402.13616

[20] Q. Zheng, J. Ma, M. Liu, Y. Liu, Y. Li, and G. Shi, "Lightweight Hot-Spot Fault Detection Model of Photovoltaic Panels in UAV Remote-Sensing Image," *Sensors,* vol. 22, no. 12, Jun. 2022. Available: doi: 10.3390/s22124617.

[21] S. Jumaboev, D. Jurakuziev, and M. Lee, "Photovoltaics Plant Fault Detection Using Deep Learning Techniques," *Remote Sens (Basel),* vol. 14, no. 15, Aug. 2022. Available: doi: 10.3390/rs14153728.

[22] L. Pratt, J. Mattheus, and R. Klein, "A benchmark dataset for defect detection and classification in electroluminescence images of PV modules using semantic segmentation", *Systems and Soft Computing,* vol. 5, p. 200048, 2023. Available: , doi: 10.1016/j.sasc.2023.200048.