

Hotspot detection on photovoltaic panel using YOLOv5s and YOLOv8s: a deep learning-based analysis

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ARTICLE INFO

Article history:

Received 21 January 2026

Revised 1 August 2026

Accepted 15 August 2026

Online first 25 September 2026

Published 25 September 2026

Keywords:

Photovoltaic (PV) Panels

Hotspot Detection

YOLO

Deep Learning

Infrared Image

Spatial Analysis

Temporal Analysis

DOI:

10.24191/esteem.v22iSeptember.10
215

ABSTRACT

This research paper explores hotspot detection on photovoltaic (PV) panels using two variants of the YOLO (You Only Look Once) algorithm: YOLOv5s and YOLOv8s. Cracking, shading, or soiling may lead to hotspots on solar panels, causing lower power output on a particular spot. Early identification of these hotspots can help maintenance operator avoid more losses while maintaining efficiency. The study uses infrared images to locate hotspots, and the dataset is annotated and split into three sets: training (70%), validation (20%), and testing (10%) for developing the YOLO models. Both models use the same procedures for hotspot detection and continuing tuning to improve the model performance. Both models performed well in terms of precision, recall, F1 score, and mean average precision (mAP), all of which were above 70%. Particularly, YOLOv5s obtained an accuracy of 89.8%, while YOLOv8s attained 88.7%. These findings show both variants of YOLO are useful for detecting and localizing hotspots in PV panels, providing an accurate method for improving solar panel maintenance and performance.

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1. INTRODUCTION

Photovoltaic panels are a cutting-edge technology that harnesses renewable energy, such as solar, to generate electrical power and are becoming increasingly popular for their cost savings and environmental benefits [1]. Over time, various factors can impact their performance, such as soiling, cell mismatches, shading from tree or building and bird dropping [2, 3]. Temperature differences on the PV panel's surface can cause these defects to spread throughout the cells. Nowadays, solar energy is more cost-effective and environmentally friendly than other energy sources; it is crucial that any potential damage over time is handled [2]. To ensure that the panels run effectively and continue to supply clean energy for many years to come, proper maintenance and monitoring are necessary.

Surface damage on PV panels, such as cracks, soiling, and shade from trees or buildings, can raise temperatures and reduce energy output, causing hotspots [2]. Hotspots are enhanced when the solar panels detect lower power output in a certain area [2, 3]. These hotspots can impact by reducing the panels electricity generation capacities [4, 20]. Identifying these unsafe locations with increased temperature is necessary. The solution is to detect hotspots on PV panels using infrared thermography images and a deep learning algorithm known as You Only Look Once (YOLO). This research aims to develop an efficient detection algorithm to identify hotspot regions using YOLO. This research will compare the performance between two different versions of YOLO to determine accuracy of which version of YOLO is more accurate in detecting hotspots.

This research focuses on developing a hotspot detection system for PV panels, with temperature as a factor affecting PV panels' output. As temperature increases, the output power decreases [5, 6]. The intention is to make it easier for consumers to clean, check, or replace the PV panels [4, 7]. Effective monitoring can help consumers save money on unnecessary repair costs and ensure optimal performance of the PV panels. The significance of this research to show ability to detect any faults which is hotspot on solar panels. This research intends to improve hotspot detection identification by including the YOLO algorithm into the detection system. The method that used thermal imaging camera to produce thermogram of radiation. These thermography images may detect defects, even in a smaller cell, providing accurate and comprehensive of PV panels surfaces.

2. BACKGROUND

2.1 Infrared Thermography

Transformation of temperature distribution from detected infrared energy into an image is a technique to display temperature variations [8, 9]. This technique is quite effective for detecting hotspot in PV modules since hotspot on the panel surface will have different temperatures. Infrared thermography displaying temperature distribution as an infrared image, can effectively locate and localize hotspot that may indicate faults with the module [1, 4].

Thermal imaging camera is a device to detect infrared radiation emits by objects to transform it into an image that displays temperature variation. This device is now regarded as a device that fast and capable tool for damage detection [1]. Normally, there are two main types of thermal imaging cameras are used for a wide range of application which is uncooled and cooled detector thermal imaging cameras.

The uncooled camera is designed based on a microbolometer and has a small vanadium oxide resistor with a higher temperature coefficient. It operates effectively in ambient conditions and is generally cheaper, offering a longer service life under similar conditions. However, the disadvantages of this uncooled detector include emitting a lower-quality image and having less sensitivity [5]. A cooled thermal imaging camera, on the other hand, is more expensive than an uncooled detector because it has an imaging sensor with a cryogenic cooling system to reduce thermal noise and increase the sensitivity of the infrared detector [5].

2.2 Hotspot

Hotspots exist when a fault in a PV module affects its ability to generate electricity [4]. Various faults may lead to hotspot, with cracks being the most primary issue. These defects act as a load, focusing current in the damaged area, resulting in significant power dissipation and the formation of a hotspot. As a result, the efficiency of the PV module decreases because of the output power decrease [3-5].

Another common defect is shading, which can be caused by a nearby building, a tree, dirt, or any other obstruction that prevents the PV module from being exposed to solar [4, 20]. When there was one cell on a PV module is shaded, it can affect the other cells by reducing the current [3, 4]. A good cell will produce higher voltage and reverse-bias the bad cell [4]. The defective cell experiences higher power dissipation, resulting in overheating and formation of hotspots.

Replacing a PV panel due to a hotspot can be rather pricey [10]. Table 1 shows an option for managing with various level hotspot. At Level 1, if the hotspot temperature exceeds 90 degrees, the PV panel must be replaced immediately. For Level 2, with temperatures between 80 to 90 degrees, the panels need to be clean and remove for inspection. At Level 3, when the temperature range 50 to 80 degrees, the PV panel should be cleaned and monitor the hotspot's temperature continuously. This action helps to minimize unnecessary repair costs.

Table 1. Level temperature range

Level	Temperature Range	Action
1	> 90°C	Replace PV panel immediately [10]
2	80 °C – 90 °C	Clean the panel and remove it for inspection [10]
3	50 °C – 80 °C	Clean the panel and continue monitoring [10]

2.3 YOLO

You Only Look Once, or has been known as YOLO, is a deep learning process that can detect and classify objects either in images and videos [11, 12]. Nowadays, YOLO has evolved through various versions and model sizes, each of it introducing improvement in speed and accuracy [11]. Table 2 below shows the progression of model sizes for YOLOv5 and YOLOv8, highlighting their different model sizes, speed, and accuracy.

Table 2. Progression of model sizes for YOLOv5 and YOLOv8

Model Version	Model Sizes	Description
YOLOv5	YOLOv5n	Smallest, fastest and less accurate [11-13]
	YOLOv5s	Lightweight, fast, and speed-critical application [11-13]
	YOLOv5m	Medium, balanced speed and accuracy [11-13]
	YOLOv5l	Higher accuracy, larger, and slower [11-13]
	YOLOv5x	Largest, most accurate, and slowest [11-13]
YOLOv8	YOLOv8n	Smallest, fastest, and less accurate [11-13]
	YOLOv8s	Lightweight, fast, and better than YOLOv8n [11-13]
	YOLOv8m	Medium, balanced speed and accuracy [11-13]
	YOLOv8l	Larger, slower, and higher accuracy [11-13]
	YOLOv8x	Largest, most accurate and slowest [11-13]

3. METHODOLOGY

The process for hotspot detection on PV panels using YOLO involves infrared images of the PV panels, training a YOLO model using labelled images, and testing its efficiency. The trained model will be utilized to identify hotspot in a new image and classify them based on location.

3.1 Flowchart

To determine hotspots on PV panels using YOLO, it needs to go through the comprehensive process depicted in Fig. 2. This process begins with loading the raw dataset and proceeds through data pre-processing, which is necessary for building an efficient YOLO model. The model is trained, validated, and tested on new images following pre-processing. The YOLO model's is well-equipped to accurately detect and localize hotspots on the PV panels by following this procedure, proving its performance and reliability.

Load Dataset

The primary goal of this research is to localize specific location on PV panels have hotspot. Initially, the images are displayed in their raw format. The total number of sample images taken is 886 images. They transform into infrared thermography image using a FLIR (Forward Looking Infrared) camera before data pre-processing. This conversion is necessary for accurately identify and analyses hotspot on the PV panels.

Data Pre-Processing

The utilization of Thermal Imaging Camera like FLIR is to obtaining image datasets in thermographic form. FLIR (Forward Looking Infrared) is a technology to produce infrared thermography image emitted from temperature distribution of an object or a scene. Here is the pre-processing step, where the step including transform a raw image into a thermography image. This helps operators find defects on PV panels with the naked eye by viewing infrared thermography images. They can identify the hotspot based on the obviously existence of fault clearer.

YOLO Model Development

YOLO has various versions and model sizes, with undergoing significant modification for a better performance and flexibility. These developments make YOLO highly useful for tasks, including object detection, tracking, segmentation, classification, and pose prediction. Each version improves both in accuracy and speed, resulting faster in detection of object [11, 19]. This ongoing evolution reveals YOLO’s flexibility and powerful capabilities in the domain of computer vision.

YOLO frameworks share a standard macro-architecture divided into three main components called backbone, neck and head. The specific architectural evolutions from standard YOLO to YOLOv5s and YOLOv8s focus on reducing computational complexity while increasing accuracy through optimized convolutional blocks and modified pooling layers [12]. Fig. 1 and Table 3 outline the core structural variations between the variants of YOLOv5s and YOLOv8s across their primary architectural blocks.

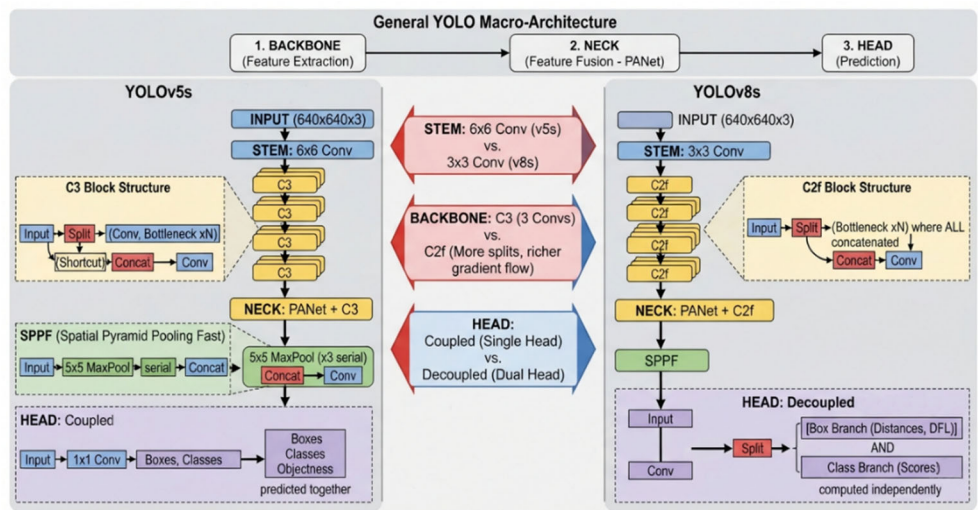


Fig. 1. Comparative architecture of YOLOv5s vs. YOLOv8s

Table 3. The architectural structural breakdown of YOLOv8s and YOLOv5s [12]

Architectural Component	YOLOv5s Structural Component	YOLOv8s Structural Component	Operational and performance impact
Initial Layer (Stem Block)	6x6 Convolution (with stride 2)	3x3 Convolution (with stride 2)	YOLOv8s uses smaller filters to extract more granular, high-resolution spatial details directly from input images compared to later versions of YOLOv5.
Primary Backbone Blocks	C3 Block (CSP Bottleneck with 3 Convolutions)	C2f Block (CSP Bottleneck with 2 Convolutions + Fast Gradient Flow)	The C2f block splits tensor channels to concatenate intermediate flows. This allows richer gradient information to pass through fewer convolutional layers.
Spatial Pooling Layer	SPPF (Spatial Pyramid Pooling Fast)	SPPF (Spatial Pyramid Pooling Fast)	Both utilize serial 5x5 max pooling layers to match the receptive field of a massive 13x13 pooler with significantly reduced compute times.
Prediction Head Type	Coupled Head	Decoupled Head	YOLOv5s uses one convolutional layer for both classes and coordinates based on preset anchors. YOLOv8s splits these into separate tracks for faster convergence.

The image datasets are annotated using LabelMe, an offline annotation tool. This task requires meticulous attention because it involves annotating about 886 images by drawing bounding boxes around the hotspots and assigning the class labels to each one. Hotspots will be classified as '1' while the background will be identified as '0'. This annotation process is essential for training the model precisely and ensuring accurate performance in the object detection task.

Consider a packed space in the image; it requires annotating images cautiously with a keen eye for detail. As this step carefully marks up these images, exporting the annotation images into YOLO label format typically includes class labels, bounding box coordinates, and confidence scores in an ensemble dataset. These exported files must be in the same directory as the images, with the same filename but a different extension (e.g., .txt). It needs to be checked a few exported annotation files to ensure that the files follow the YOLO format.

Once the dataset is properly annotated, the next step is to split the dataset into three sections: training, validation, and testing. The training set contains 70% (620 images). The validation set covers 20% (177 images), and the remaining 10% (89 images) is used for the test set. This section ensures that the model is properly trained, tuned, and evaluated for accuracy, which leads to a comprehensive evaluation of its performance.

Tune Model

In machine learning, tuning a model is to adjust the settings to make the model perform better on a specific task [14]. Especially to make the model predict the outcome more accurately. The model performance on a dataset can improve by adjusting hyperparameters based on the learning rate, batch size, image size and various architectural parameters like the number of layers. This helps develop an efficient and accurate hotspot detection system.

Train, Validate and Test

The primary dataset is used to adapt the machine learning model with the utilization of the YOLO training script from Ultralytics. It trains the model on the data's basic structure and connections. The model learns from the training data by changing parameters, such as weights and biases, to decrease the error between the predictions and actual target values. Validation data is used to train the model's performance by using separated dataset from the training data, and the model do not learn directly from it. The accuracy of detection can be improved with the accuracy of annotation. The test data is used to present a final, objective assessment of the trained and tuned model. It's like using unseen data that the model never encountered to ensure it can apply well to a new situation.

Hotspot Detection and Localisation

When it tests on a new image that has not been used in training and validation, the model can detect hotspots on a PV panel and localise the exact area where the hotspots occur. This capability shows the model's ability to detect and localise defects in previously unknown data, ensuring its accuracy and reliability.

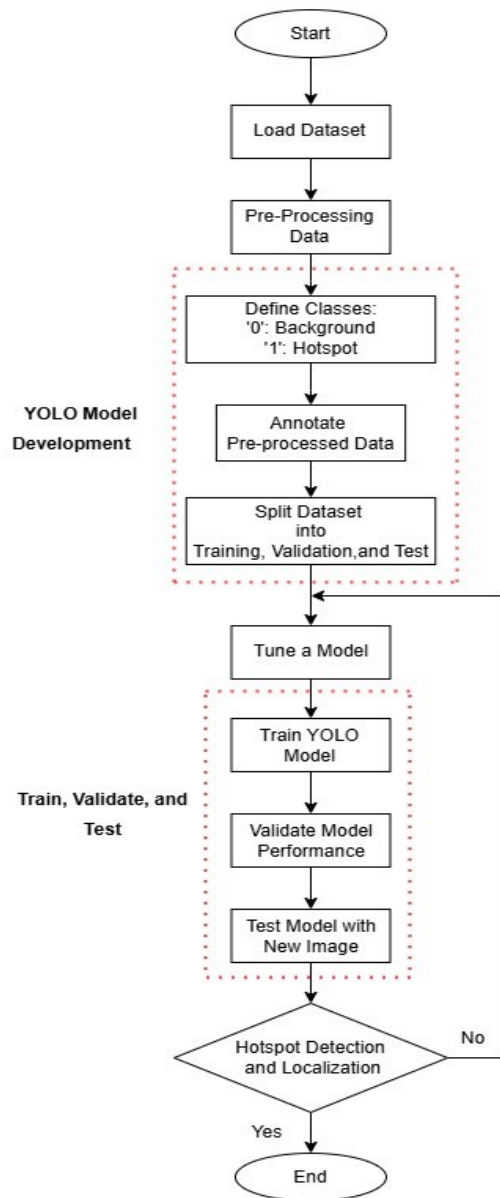


Fig. 2. Flowchart of overall process for hotspot detection using YOLO models

3.2 Spatial and Temporal Analysis

Object detection is the process of identifying and localising specific targets within an image or video [15]. In contrast to image classification, which only identifies the presence of an object, object detection simultaneously determines semantic categories and physical locations by generating

bounding boxes around each detected instance. This study utilises the YOLO framework for object detection due to its unified architecture. Specifically, YOLO employs a convolutional neural network (CNN) for feature extraction alongside regression networks to precisely determine the bounding box coordinates for each detected object [15, 16, 19].

Spatial Analysis

The goal of this research is to detect hotspots on PV panels by predicting their bounding boxes, a process called spatial analysis. The input image is divided into an $S \times S$ grid, where each grid is responsible for predicting the presence of a hotspot. Each grid cell predicts bounding boxes and confidence scores for those boxes. Each bounding box contains coordinates (x, y, width, height), giving exact localisation of hotspots in the images [16, 17].

The following equation is used to convert the predicted values to absolute pixel coordinates, increasing the accuracy of hotspot localization on PV panels. By converting these expected values, we can precisely calculate the position and dimensions of each bounding box in the image. This method is essential for effective spatial analysis since it allows us to find hotspots with great precision. As a result, the precise coordinates (x, y) and dimensions (width, height) generated by this conversion provide vital data for maintaining and optimizing the performance of PV panels.

$$b_x = \sigma(t_x) + c_x \quad (1)$$

$$b_y = \sigma(t_y) + c_y \quad (2)$$

$$b_w = \rho_{we} t_w \quad (3)$$

$$b_h = \rho_{he} t_h \quad (4)$$

Equations (1) and (2) show the centre coordinates of the bounding boxes, while (3) and (4) indicate the boxes' width and height. In these equations, t_x , t_y , t_w , t_h are the predicted values; c_x , c_y are the coordinates of the top-left corner of the grid cell, and p_w , p_h are the width and height of the anchor box. These conversions are needed to convert the model's prediction into absolute pixel coordinates, which enables precise hotspot localisation on PV panels.

$$IoU = \frac{\text{Area of Intersection}}{\text{Area of Union}} \quad (5)$$

The Area of Intersection is the overlapping area between the predicted and ground truth boxes, where the Area of Union is the combined area covered by both boxes. IoU is or Intersection over Union, is a metric that measures the overlap between predicted and ground truth boxes. IoU proves essential to evaluating the accuracy of the object identification algorithm since it evaluates how closely the predicted bounding boxes match the actual locations of the hotspots on the PV panels.

The confidence score reflects the bounding box's probability and accuracy the bounding box in locating the hotspot. This score shows how certain the model is that the region contains a hotspot and how accurately the bounding box determines its position. High confidence scores imply accuracy and reliable detection, which is key for effective hotspot identification on PV panels.

$$\text{Confidence} = \text{Pr}(\text{Object}) \times \text{IoU} \quad (6)$$

Where $\text{Pr}(\text{Object})$ is the probability that an object exists in the box, and IoU is the IoU between the predicted box and ground truth.

These equations are important to the operation of YOLO in spatial analysis for object detection, ensuring accurate localisation and classification of objects within images.

Temporal Analysis

Temporal analysis means analysing data over time to identify patterns and trends in PV system. This method seeks to improve the accuracy and efficiency of hotspot detection by using temporal data. By analysing modifications and developments over time, it can better understand and predict the formation of hotspots, leading to more effective PV panel maintenance and optimisation.

In this case, temporal analysis involves analysing changes in temperature and hotspot patterns over time. Hotspots are usually linked with higher temperatures on PV panels, which can change over time. It can identify hotspots and patterns by evaluating the historical data [8] on temperature variation and hotspot occurrences. This research helps in understanding the temporal pattern of hotspots, resulting in more accurate predictions and improved management of PV panel performance.

Deep learning methods, such as YOLOv5 and YOLOv8, combined with infrared imaging, enable efficient and accurate hotspot detection in PV panels. This method can evaluate high-dimensional data from infrared images and improve the durability and accuracy of hotspot detection, even in challenging situations. This robust detection allows a quick identification of hotspots, leading to better maintenance and performance optimization for PV systems. Incorporating and processing cloud data provides an infrared PV panel image dataset, which makes it an excellent tool for training and testing the hotspot identification algorithms.

4. RESULTS AND DISCUSSION

The implementation of YOLO for hotspot detection on PV panels requires gathering high-resolution infrared images, training the YOLO model on labelled images, and validating its effectiveness. The trained model is then used to detect hotspots, identifying them based on location to allocate maintenance. This methodology increases accuracy and efficiency, besides reducing the need for manual inspection.

4.1 Experimental Results

The main goal of this research is to detect hotspots on PV panels using YOLO, an important step in ensuring the efficiency and reliability of solar energy systems. The dataset was systematically split into training, validation, and test sets, which were labelled into two classes: background and hotspot.

In order to achieve accurate localisation and identification of hotspots, this study recorded ground truth bounding boxes in the format (x, y, width, height), where (x,y) represents the top-left corner of each bounding box. This accurate process provides a solid basis for accurate hotspot detection, therefore improving performance and efficiency in PV panel monitoring. YOLO offer pre-trained models of various sizes such as, nano, small, medium, large, and extra-large; however, the performance of nano, small, and medium models [17]. Surprisingly, no significant improvements were detected, leading to the use of the small model for this study.

Fig. 2 and Fig. 3 show the experimental results for the YOLOv8s and YOLOv5s models. Fig. 2(a) and Fig. 3(a) display the training image datasets used localize hotspot, while during the training phase, the used of weights from a previously trained model, as shown in Fig. 2(b) and Fig. 3(b), proved the training process effective. Moreover, Fig. 2(c) and Fig. 3(c) display the model's ability to detect and localise hotspots on a PV panel using a new image, proving its practical application and accuracy. These results prove the usefulness of YOLO in hotspot detection, paving the way for improved monitoring and maintenance processes in solar energy systems.

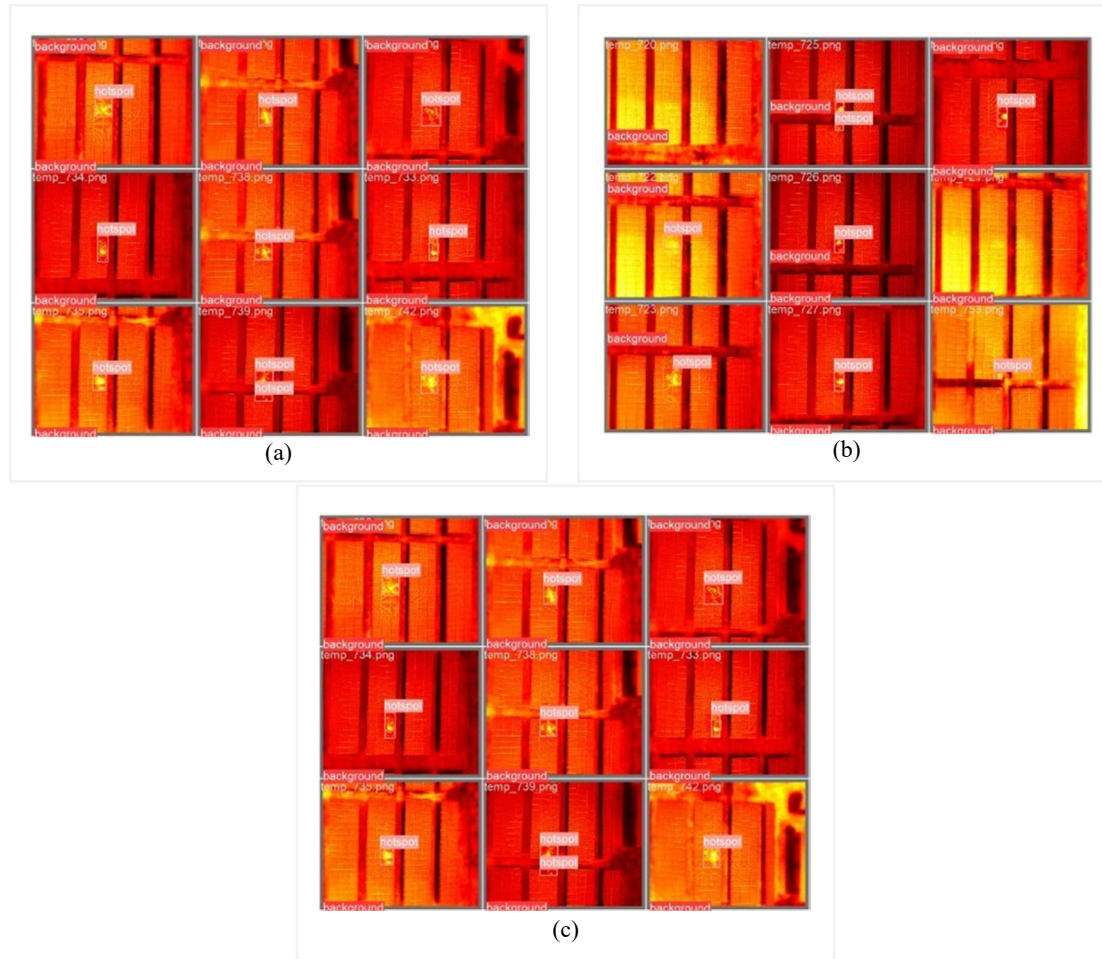


Fig. 2. Train, Validate and Test (a–c) for hotspot detection using YOLOv8s

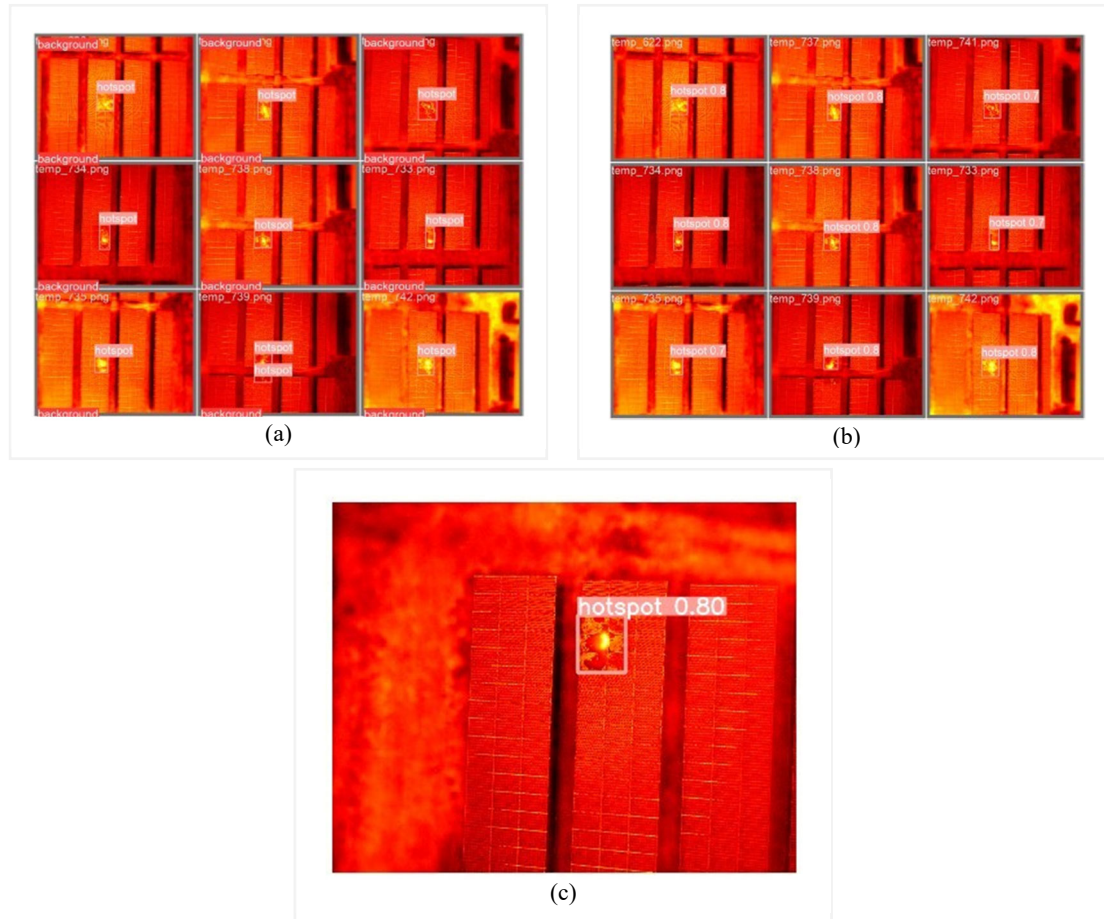


Fig. 3. Train, Validate and Test (a–c) for hotspot detection using YOLOv5s

4.2 Accuracy

Indeed, the confusion matrix includes important measures such as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), which are important for evaluating a model's precision and recall, displaying its ability and accuracy [14, 18]. TP are situations in which the model accurately detects hotspots on PV panels. TN are situations where the model correctly identifies areas without hotspots. FP are cases where the model incorrectly labels a non-hotspot area as a hotspot, and FN are cases where the model fails to identify a true hotspot [14]. panels.

$$Precision, (P) = \frac{TP}{TP + FP} \quad (7)$$

Precision (P) is calculated as the ratio of TP to the sum of TP and FP, indicating the model's ability to accurately detect hotspots without misleadingly classifying non-hotspot areas [14, 18].

$$\text{Recall, (R)} = \frac{TP}{TP + FN} \quad (8)$$

Recall (R), also known as sensitivity or true positive rate, analyses the model's ability to detect all actual hotspots by dividing TP by the sum of TP and FN [14, 18].

$$F1 \text{ Score} = 2 \times \frac{(P \times R)}{(P + R)} \quad (9)$$

The F1 score is the harmonic mean of precision and recall, combining the two metrics to get a single value that indicates the model's overall performance [14, 18].

$$\text{Accuracy} = \frac{IoU}{\text{Total no. of prediction}} \quad (10)$$

The intersection over union (IoU) is important information for determining the similarities between detected bounding boxes and annotated ones. It determines the percentage of overlap, ranging from 0 (no overlap) to 100% (perfect overlap) [17, 20]. YOLOv8s and YOLOv5s have calculated IoU of 80% and 79%, respectively, showing a near-perfect overlap between the detected and annotated bounding boxes. This high level of compatibility shows the model's accuracy in detecting hotspots on PV panels.

To achieve good accuracy, the model must detect hotspots with high precision and recall, both exceeding 70%. This indicates the model's ability to correctly identify and precisely locate the hotspots in the image. Table 4 shows the precision, recall, mAP50 (mean average precision), IoU, and accuracy, all of which exceed 70% for both the YOLOv8s and YOLOv8m models. These results verify the model's performance in hotspot detection and localisation, increasing confidence in their use for PV panel monitoring and maintenance tasks.

Table 4. The results of YOLOv8s and YOLOv5s

Model	P (%)	R (%)	mAP50 (%)	IoU (%)	Accuracy (%)
YOLOv8s	90.4	77.3	83.33	79.0	88.7
YOLOv5s	82.0	77.6	79.74	80.0	89.8

Utilising equation (10) and a total of 89 predictions, the results show a small 1.1% difference in accuracy across the models. Surprisingly, YOLOv5s has a dominant accuracy of 89.8%, while the other version, YOLOv8s, is closely behind with an outstanding 88.7%. This slight difference shows the different details in model performance, which represent the complex combination of structure and optimisation methods. Despite this slight difference, both models show an impressive ability to detect and localize hotspot on PV panels with high precision. Such a complex result not only improves the understanding of deep learning methods, but also shows the potential of advanced algorithms to improve renewable energy monitoring and maintenance processes.

5. CONCLUSION

In conclusion, the goal of this research is to use the YOLO method to efficiently detect hotspot regions. YOLO specialises in object detection by categorising and locating objects using bounding boxes around hotspots. The results show outstanding accuracy approaching 100%, even using different versions of YOLO, which is YOLOv5s and YOLOv8s. This significant level of accuracy, especially in complex locations, shows the ability of current algorithms to greatly improve monitoring and maintenance of PV panels. Further research attempts should focus on implementing and evaluating both models in real-world situations to ensure their efficiency and locate possible hotspots for further improvement. Through the implementation of these models in actual environments, it can obtain significant information about the effectiveness of the model functions in real-world situations.

6. ACKNOWLEDGEMENTS/FUNDING

The authors wish to thank Universiti Teknologi MARA (UiTM), Cawangan Pulau Pinang, Malaysia, as well as Electrical Engineering Studies, Universiti Teknologi MARA Cawangan Pulau Pinang, Permatang Pauh Campus, 13500 Seberang Perai, Pulau Pinang, Malaysia, for all the support and funding given during this research. The authors extend their heartfelt gratitude to Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA) and Universitas Muhammadiyah Semarang (UNIMUS) for generously providing financial support through the Matching Grant under Grant No. RDU242729/UIC241531.

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

Nurul Izzah Idayu Mohd Zaki: Conceptualisation, methodology, formal analysis, investigation and writing-original draft; **Kamarulazhar Daud:** Supervision, conceptualisation, writing- review and editing, and validation; **Muhammad Khusairi Osman:** Supervision, formal analysis and validation; **Mohd Zulhamdy Ab Hamid:** Conceptualisation, methodology, and formal analysis; **Iza Sazanita Isa:** Conceptualisation, formal analysis, and validation; **Zainal Hisham Che Soh:** Conceptualisation, formal analysis, and validation; **Saodah Omar:** Conceptualisation, and formal analysis; **Abdul Malek Saidina Omar:** Conceptualisation, and formal analysis; **Mohd Shawal Jadin:** Conceptualisation, formal analysis, and validation.; **Sabhan Kanata:** Formal analysis, and validation.

9. DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

During the preparation of this work, the author(s) used Quillbot to checks for punctuation errors, vocabulary usage, rewrite, and change the tone of the text to improve clarity. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

10. DATA AVAILABILITY/SUPPLEMENTARY MATERIALS

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

11. ETHICS STATEMENT

The authors declare that this research did not involve human or animal subjects. All experimental procedures were performed following the institutional Safety, Health, and Environmental (HSE) protocols of Universiti Teknologi MARA (UiTM).

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