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Solar Panel Defect Detection using FOMO on Edge Impulse

Muhammad Nabil Aiman Baderul Hisham, Roslan Seman, Zuraidi Saad, Zainal Hisham Che Soh*
*Corresponding Author

Electrical Engineering Studies, College of Engineering,
Universiti Teknologi MARA,Cawangan Pulau Pinang, Permatang Pauh, Malaysia

E2020828696@student.uitm.edu.my, rosem@uitm.edu.my, zuraidi570@uitm.edu.my & zainal872@uitm.edu.my
Tel: 03-3822532

Abstract
A machine learning model is developed for detecting defects in solar panels, focusing on hotspot detection. The project was created on Edge Impulse with images of solar panels in normal and defective states. The trained model with appropriate training accuracy was then deployed on a smartphone for real-time defect detection, utilizing a camera to capture and process image frames, overlaying results on a smartphone screen for immediate inspection. The evaluation revealed an F1 score of 80.5% for hotspot detection with an accuracy of over 95% for the model-detecting hotspots. This demonstrates the model's practical application and effectiveness for solar panel hotspot detection.

Keywords: Solar Panel Defect Detection, Hotspots and Crack Defect, Faster Object More Object (FOMO), Edge Impulse

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1.0 Introduction

As the world shifts towards renewable sources of energy, solar power emerges as a key player in the energy revolution. The efficiency and longevity of solar panels, however, are compromised by physical defects like hotspots and micro-cracks, which can lead to reduced output and premature panel failure. These defects not only shorten the panels' lifespan and limit their energy output but also accelerate their disintegration, resulting in substantial financial losses. Traditional detection techniques are largely manual, time-consuming, and prone to errors, making it difficult to implement effective preventive maintenance strategies. With the traditional inspection techniques which are labor-intensive and frequently inaccurate, more advanced detection techniques are now possible thanks to recent developments in deep learning and image processing technologies. Using a FOMO-based object identification model on the Edge Impulse platform, this research aims to take advantage of these technologies by providing an alternative method for identifying and evaluating solar panel flaws. The project aims to solve solar panel defects by using a machine learning algorithm FOMO (Faster Object, More Object) with the Edge Impulse platform to detect defects on solar panels. Furthermore, this research aims to enhance the accuracy and ease the detection process by deploying the object detection model on smartphones for real-time defect detection.

This paper presents a Solar Panel Defect Detection Using FOMO on Edge Impulse. The remainder of the paper is organized as follows. Section 2 describes the research background and literature review related to this research work. Section 3 presented the methodology approach for this research work. Section 4 discussed the experimental result of Solar Panel Defect Detection Using FOMO on Edge Impulse performance. Finally, section 5 provides the concluding remarks and points out the ideas for future extension of this work.

2.0 Literature Review

Based on research done by (J. A. Dhanraj et al.,2021), a comprehensive study that integrated diverse data points, such as weather patterns and electrical outputs, with advanced diagnostic tools like infrared thermography to enhance fault detection accuracy and provide a foundation for future research in refining diagnostic methods. Research by (U. Pruthviraj et al., 2023) utilized thermal and visual imagery captured by UAVs and voltage-based hotspot detection methods to conduct an aerial thermal survey of a solar farm. This approach enabled the identification of hotspots in PV panels with 97% accuracy, showcasing the effectiveness of thermal imaging in inspecting solar photovoltaic systems and the early detection of hotspots to prevent extended damage.

Additionally, using infrared thermography (M. U. Ali et al., 2022) developed a machine-learning framework for hotspot detection in photovoltaic modules. By calculating various image features and constructing a training dataset, the proposed framework demonstrated high accuracy and effectiveness in detecting and classifying hotspots in solar panels, highlighting the potential of machine learning techniques in fault detection. Moreover, (K. A. K. Niazi et al., 2019) employed a Naive Bayes classifier to diagnose hotspots in solar PV modules using non-enhanced and non-radiometric thermal images. By extracting texture and histogram of gradient features from thermal images, the proposed methodology achieved a mean recognition rate of approximately 94.1%, showcasing its effectiveness in classifying and diagnosing hotspots in photovoltaic systems.

(F. Wang et al., 2023) F. Wang et al. introduced edge feature enhancement and infrared spatial attention modules to address challenges such as edge-blurring and the detection of small targets. Their study showed improved segmentation accuracy for hotspots in thermal infrared images compared to traditional methods, suggesting potential applications in real-world engineering scenarios. Similarly, (Z. B. Duranay, 2023) developed a novel approach using infrared solar module images, employing NCA feature selection with SVM classifiers to accurately classify photovoltaic panel defects, including hotspots with an average accuracy of 93.93%.

Machine learning frameworks have also been instrumental in advancing solar panel defect detection. (B. Sandeep et al., 2023) utilized TensorFlow to generate and classify hotspot images similar to real solar panel images. Their approach achieved a 98% accuracy in classifying and localizing hotspots. The authors highlight the speed and effectiveness of the method for quick diagnosis and immediate action to prevent panel damage. Furthermore, (S. P. Pathak et al., 2024) applied histogram-based color thresholding and RGB color channel-based thresholding to thermal images from various solar plants across India. Their comparative fault detection method improved the efficiency, reliability, and overall safety of PV systems while reducing costs and human labor.

Other notable methodologies include the work of (G. Terzoglou et al., 2023), who proposed using RGB and thermal pictures taken by drones and implementing a CNN based on YOLOv5 architecture to identify solar panel problems. Their approach successfully identified and categorized issues using advanced image preprocessing and classification techniques. Additionally, D. P. Winston et al. (2021) developed a PV hotspot fault detection algorithm using artificial neural networks (ANN) and support vector machines (SVM), with the SVM-based method effectively detecting various levels of hotspots and micro-cracks. (M. Karimi et al., 2020) proposed a current-based approach for hotspot detection in photovoltaic strings, utilizing the Teager-Kaiser energy operator technique and cumulative rate slope calculation. This method effectively detected hotspots before causing permanent damage. Other applications of computer vision on edge computing such as for riverbank monitoring (Soh et al., 2022) and the security of abandoned baggage (Soh et al., 2020).

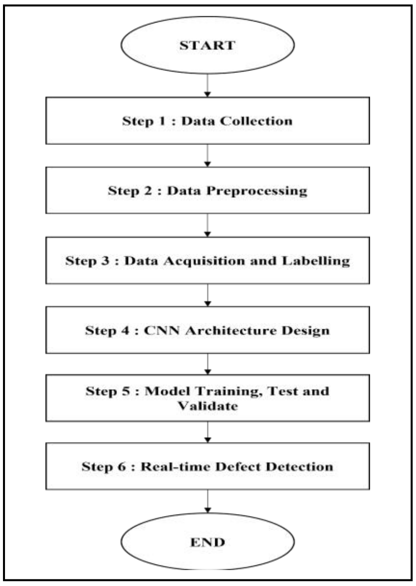


Fig. 1: Overall Steps for Solar Panel Defect Detection

3.0 Methodology

This paper presents projects that were carried out in six steps. All these steps are part of the process on the Edge Impulse platform, as shown in Figure 1 below. The flowchart shows the overall workflow involved in the solar panel defect detection system. This proposed system will be developed based on 6 phases: data collection, preprocessing, acquisition and labeling, CNN architecture design, model training, testing and validation, and real-time defect detection. The sample images with a few hotspots in the solar panel will be obtained from the database online, which is from the Kaggle website. Next, data preprocessing is required to resize images to 416x416 pixels. The images will then be uploaded to Edge Impulse for data acquisition and labeling. Next, the CNN architecture implement the FOMO algorithm for model training, testing, and validation. Model validation is then done to validate the model with a test dataset and to analyze performance metrics. Then, real-time defect detection can be done by deploying the model to edge devices such as smartphones or microcontrollers to detect defects using the deployed model.

3.1 Data Collection

The dataset is the most important in implementing computer vision and AI for developing solar panel defect detection systems. Given that solar panel images may vary in lighting and scale, standardizing the image size is essential for consistent model training. Figure 2 shows samples of the dataset used, which was obtained from an online source called “Infrared Solar Modules” from the Kaggle website, which is a trusted website to find dataset images. This dataset includes 20,000 image samples of solar panels to train, test, and validate the model, but this project only selected 100 images to train the model as proof of concept.

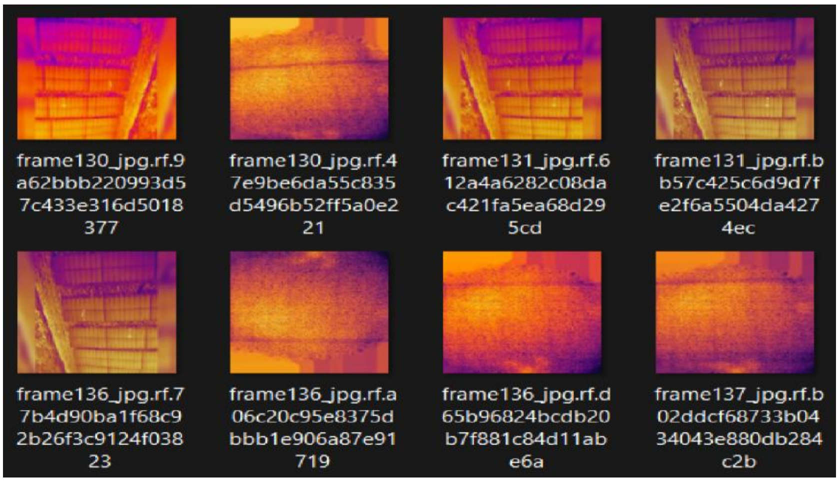


Fig. 2: Samples of the dataset Images used for Solar Panel Defect Detection

3.2 Data Preprocessing

Edge Impulse platform already providing the aids to automatically divide these datasets into training and testing sets Thus, since the images already enhanced and in same pixels size, which is 416 x 416 pixels, there is no necessities to rotate, shear or manipulate the images in any way. Figure 3 show list of some images in the datasets on data sources pages in Edge Impulse website. From the dataset for images containing solar panels with defects such as hotspots, the image in the dataset is in the dimensions of 640x640 pixels and has been reduced the dimensions to 416x416 pixels to match the normal solar panel images. Both images from the original and resized have the same horizontal resolution and vertical resolution of 96 dpi, making the quality of the image remain unchanged. The bit depth of the image also remains the same at 24 bits.

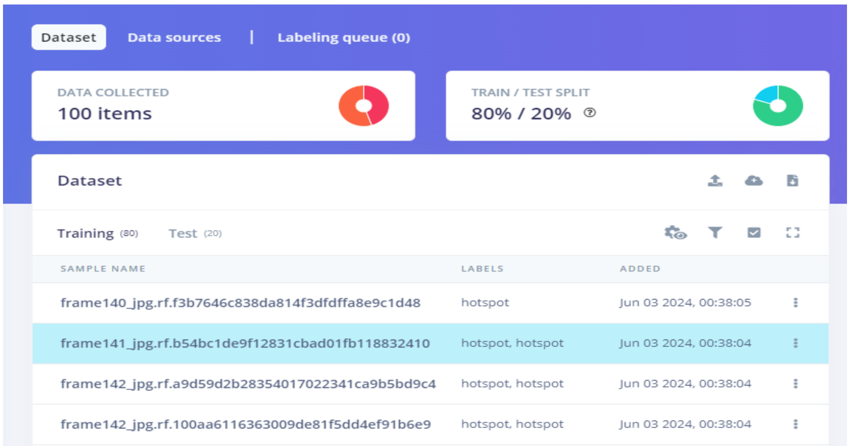


Fig. 3: List of some images in the datasets on the data sources pages in Edge Impulse

3.3 Data Acquisition and Labeling

During the image acquisition stage, it is imperative to correctly label the images with their respective defect annotations, as shown in Figure 4. These labels serve as ground truth data and are critical for training the FOMO (Faster Objects, More Objects) model. Accurate annotations ensure that the model learns to recognize and locate defects within the solar panels effectively. The labeled data is used to teach the FOMO model to distinguish between different types of defects, enabling it to detect and count multiple defects in real time using significantly less processing power and memory compared to other object detection models like MobileNet SSD or YOLOv5. By carefully managing the image acquisition and feature extraction process, we can ensure that the FOMO model is trained on high-quality data, leading to more accurate and efficient defect detection in solar panels.

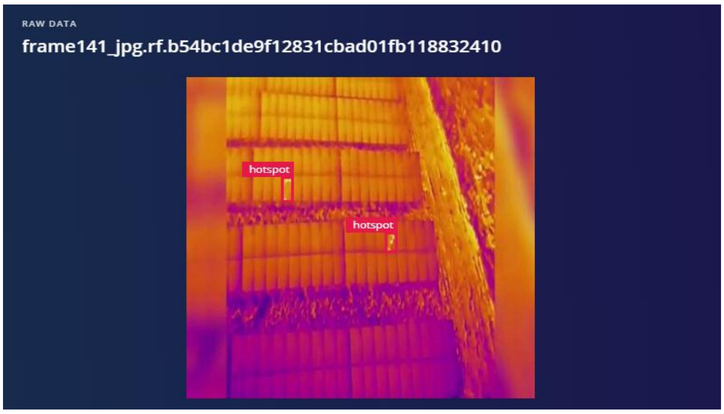


Fig. 4: Data Labeling Process using Bounding Box

3.4 CNN Architecture Design

For this project, the Edge Impulse platform was used to develop and train the CNN architecture, specifically tailored to utilize the FOMO (Faster Objects, More Objects) algorithm. FOMO uses the early layers of the MobileNetV2 network as a feature extractor, resulting in an n×n feature grid, where the size of n depends on how deep the feature extractor is. The feature grid is then fed into a small detection head that predicts object centers by classifying each of the n×n features and clustering predictions that belong to the same object. FOMO is optimized for detecting multiple objects rapidly and efficiently, making it well-suited for edge applications with resource constraints. The CNN architecture implemented is based on MobileNetV2, a lightweight and efficient model architecture designed for mobile and edge devices. MobileNetV2 is renowned for its balance between accuracy and computational efficiency, achieved through depth-wise separable convolutions and inverted residuals (I. N. Mihigo et al., 2022). The input images are resized to 416x416 pixels, with three color channels (red, green, and blue). This results in an input size of 416x416x3, equating to 519,168 features.

3.5 Model Training, Testing, and Validation

Several parameters need to be configured as well upon creating the model. First, the number of training cycles needed to be adjusted based on the model's needs. Usually, a higher number of training cycles or epochs means better model performance. However, since the limit of the Edge Impulse Community Version, which is free to use, the package only allows us to create a model of up to 20 minutes per training job in one project, meaning that the number of training cycles needed to be lowered to just 50 epochs. Next, the learning rate will control how much the model's weights are adjusted for the loss gradient. The learning rate needed to be adjusted to ensure efficient training, and as such, the learning rate used in this project was adjusted to 0.005. The validation set size also impacts the model's performance; such a validation set size is a portion of the training data put aside as validation to monitor the model's performance during training and prevent overfitting. These three parameters are the main parameters that were used to fine-tune the model's performance. Since Edge Impulse is a new platform with a user-friendly environment and an easy-to-use interface, adjusting these parameters is easy.

3.6 Real-time Defect Detection

The final step in this project involves deploying the trained model on a smartphone, fully utilizing the device's camera to capture real-time images of the solar panels. The deployed model processes each captured frame, which performs inference to detect and classify any hotspots or defects. Inference is how the trained model applies its learned features to new data to make predictions. Having a lower inference time indicates the model performance has significantly improved to the point where the user can obtain better real-time detection. The Edge Impulse platform facilitates this by optimizing the model for efficient real-time processing even on devices with limited computational power, like smartphones. The camera continuously captures frames of the solar panels in real time. Each frame is fed into the deployed model, which performs inference to detect and classify any hotspots or defects on the solar panels. The inference results, including the location of detected defects, are overlaid on the camera feed and displayed on the smartphone screen. This visual feedback allows for immediate inspection and action.

4.0 Results and Discussion

The results of the model, specifically designed for detecting hotspots on solar panels using the Edge Impulse platform, are evaluated and discussed in this section based on performance metrics, the confusion matrix, and its effectiveness in real-world scenarios. Real-world testing involves deploying the model on edge devices like smartphones to monitor solar panels under various conditions. This practical evaluation assesses the model's performance in different environmental settings, ensuring it can provide timely and accurate detection of hotspots. The model's real-time feedback allows for immediate intervention, preventing minor defects from escalating. This thorough evaluation confirms the model's strength and efficiency, demonstrating its practical application in maintaining solar panel efficiency and longevity.

4.1 Hotspot Training Model Performance

The evaluation of the model's performance includes metrics such as the F1 Score, precision, and recall. The F1 Score, the harmonic mean of precision and recall, is vital for understanding the balance between these metrics. Our model achieved an F1 Score of 80.5%, indicating a strong equilibrium between precision—the accuracy of the optimistic predictions—and recall—the model's ability to capture all relevant instances. This high F1 Score suggests that our model is proficient at both identifying true positives and minimizing false negatives, which is important for effective hotspot detection in solar panels. The detailed results are summarized in Table 1 below, clearly showing the model's classification capabilities and areas for further improvement.

Table 1. Hotspot Model Training Performance and Confusion Matrix

Last training performance (Validation Set)			
Accuracy	80.5%	Loss	19.5%
Confusion matrix (Validation Set)			
	Background	Hotspot	Normal
Background	100%	0.0%	0.0%
Hotspot	23.1%	76.9%	0.0%
Normal	16.0%	0.0%	84.0%
F1 Score	1.0	0.80	0.81

4.2 Hotspot Performance Evaluation

Significant improvements were made in the model's performance throughout this project, with the F1 Score increasing from 50% to 80.5%. One of the main obstacles addressed was the initial mislabelling of normal solar panel conditions as hotspots. This misclassification issue had a huge impact because it directly impacted the model's accuracy and F1 score, as shown in Figure 5(a). The model's precision and recall improved by refining the labeling process and ensuring that the annotations correctly distinguished between normal conditions and hotspots, leading to a higher overall F1 score, as shown in Figure 5(b).

(a)

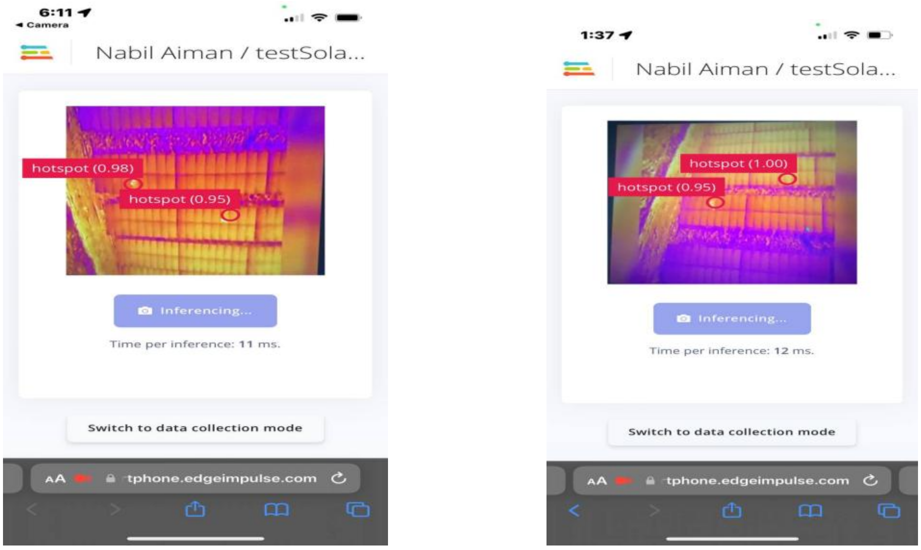
(b)

Fig. 5. (a) Initial Hotspot Model Training Performance; (b) Final Hotspot Model Training Performance.

Key to these improvements were the adjustments made to the training parameters. Specifically, setting the number of training cycles or epochs to 50 and the learning rate to 0.005 proved effective. These parameters allowed the model to learn more effectively from the data, reducing the overall loss and enhancing the model's ability to generalize from the training data. The improved performance is evident in the updated confusion matrix shown in Figure 5(b), reflecting a more accurate classification of hotspots and normal conditions. This optimized training process, combined with correct labeling and parameter adjustments, resulted in a better model capable of reliably detecting defects in solar panels. Although the dataset is small, the model achieved an F1 Score of 80.5%, indicating that the model is proficient at both identifying true positives and minimizing false negatives, which is important for effective hotspot detection in solar panels. Then, real-time defect detection can be done by deploying the model on a smartphone.

4.3 Live Classification Performance

The primary goal of this analysis is to evaluate the model's real-time performance. The live classification of solar panel defects showcases the model's ability to make decisions in real-time. The model achieved impressive accuracy levels of 0.98 and 0.95, indicating over 95% accuracy. Furthermore, the model demonstrated a fast response time of around 11 to 12 milliseconds. In machine learning and real-time detection applications, a millisecond response time is considered exceptionally fast, underscoring the model's efficiency.



(a) (b)

Fig. 6. Live Classification of Solar Panel Showing Hotspot Detection using Smartphone (a) Inference time 11s; (b) Inference time 12s.

During inference, the model analyses each frame to identify features indicative of hotspots or defects. The model's training allows it to accurately distinguish between normal conditions and potential issues on the solar panels. Classifying and locating defects in real-time is a critical feature, enabling immediate detection of problems. The results of the inference, including the location of detected defects, are overlaid on the live camera feed, like in Figures 6(a) and 6(b). This overlay provides visual markers on the smartphone screen, highlighting areas of concern directly on the captured image. This real-time visual feedback is invaluable for inspectors or technicians as it allows them to see precisely where the defects are located without manually analyzing the data. Users can immediately inspect the identified hotspots or defects with the visual feedback displayed on the smartphone screen. This rapid detection and visualization enable quick decision-making and action, such as scheduling maintenance or repairs in real-life scenarios. The ability to address issues promptly helps maintain the solar panels' efficiency and longevity, preventing minor defects from escalating into major problems.

5.0 Conclusion & Recommendations

To conclude this research, this project successfully developed and implemented a solar panel defect detection system using the FOMO algorithm on the Edge Impulse platform. The system was tailored to identify hotspots with high accuracy and efficiency, aiding in solving issues that arise in photovoltaic maintenance. By employing the lightweight MobileNetV2 0.35, which is FOMO architecture, the model achieved a significant balance between computational efficiency and detection accuracy, making it well-suited for deployment on edge devices with limited resources. Integrating depth-wise separable convolutions and inverted residuals in MobileNetV2 contributed to this efficiency, enabling real-time defect detection.

The model's performance was evaluated through various metrics, with an F1 score of 80.5% and an inference time of 10 - 20 milliseconds, demonstrating its capability to provide fast and accurate defect detection. The confusion matrix further highlighted the model's proficiency in distinguishing between hotspots and normal areas with a high level of accuracy. This performance underscores the potential of machine learning in enhancing the reliability and efficiency of solar energy systems. As for recommendations, future work will focus on enhancing the defect detection capabilities of the current system by incorporating crack detection alongside hotspot detection. By expanding the scope to detect other defects like cracks, the system aims to provide a more comprehensive solution for solar panel maintenance, contributing to solar power systems' sustainability and longevity.

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Paper Contribution to Related Field of Study

The study's purpose is to enhance the reliability and efficiency of solar panels, ensuring the energy they provide is maintained at its optimum level. This research is expected to offer significant contributions to the field of photovoltaic maintenance by not only improving defect detection rates but also by serving as a benchmark for future innovations in the sector.

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