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Deep learning based fault detection and diagnosis in photovoltaic system using thermal images acquired by UAV

İHA tarafından elde edilen termal görüntüler kullanılarak fotovoltaik sistemde derin öğrenme tabanlı arıza tespiti ve teşhisi

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Deep Learning Based Fault Detection And Diagnosis in Photovoltaic System Using Thermal Images Acquired by UAV

Highlights

- *Photovoltaic system*
- *Thermography*
- *Deep learning*
- *Fault detection and diagnosis*
- *Unmanned aerial vehicles*

Graphical Abstract

In this study, it is discussed to detect cell, module and panel faults in panels using thermal images obtained from solar panels. Within the scope of the study, a four-rotor unmanned aerial vehicle (drone) was designed and a thermal camera was placed on the vehicle.

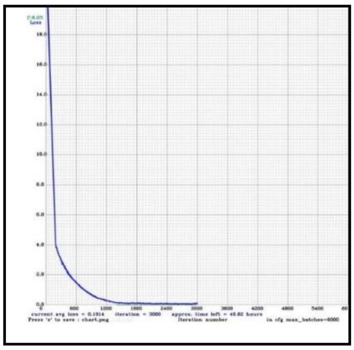

Figure. Training loss graph.

Aim

In this study, thermal images of solar panels are taken by unmanned aerial vehicle and errors on solar panels are detected and diagnosed.

Design & Methodology

In this study, a four-rotor UAV is used to obtain the thermal image of the solar panels. Equipped with a thermal camera, the UAV performs autonomous flights on solar panels.

Originality

The use of artificial intelligence in the detection and diagnosis of these faults increases the success rate. The use of drones during the acquisition of thermal images ensures a fast and error-free result.

Findings

In the experiments conducted after the completion of the training, 97% accuracy in the detection and diagnosis of cell fault, 95% in the detection and diagnosis of module fault, and 93% in the detection and diagnosis of panel fault was determined.

Conclusion

As a result of the tests with thermal images, it is seen that the accuracy rates obtained in the Yolov3 network are sufficient.

Declaration of Ethical Standards

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Deep Learning Based Fault Detection and Diagnosis in Photovoltaic System Using Thermal Images Acquired by UAV

Araştırma Makalesi / Research Article

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ABSTRACT

Solar power is one of the largest renewable energy sources in the world. With photovoltaic systems, electrical energy can be generated wherever the sun is located. To prevent efficiency losses in photovoltaic systems, these systems should be tested at regular intervals. In this study, it is discussed to detect cell, module and panel faults in panels using thermal images obtained from solar panels. Within the scope of the study, a four-rotor unmanned aerial vehicle (drone) was designed and a thermal camera was placed on the vehicle. Thus, thermal images of the solar panels on the roof of Karabuk University buildings were taken. A thermal data set with cell fault, module fault and panel fault were created using the resulting thermal images. The YOLOv3 deep learning-based convolutional neural network was trained with the created dataset. This training was conducted on Nvidia Jetson TX2, an embedded AI (Artificial Intelligence) computing device. After the completion of the training of the YOLOv3 network, it was concluded that the faults mentioned in the tests were successfully detected.

Keywords: Photovoltaic system, thermography, deep learning, fault detection and diagnosis, unmanned aerial vehicles.

İHA Tarafından Elde Edilen Termal Görüntüler Kullanılarak Fotovoltaik Sistemde Derin Öğrenme Tabanlı Arıza Tespiti ve Teşhisi

ÖZ

Güneş enerjisi, dünyanın en büyük yenilenebilir enerji kaynaklarından biridir. Fotovoltaik sistemler ile güneşin olduğu her yerde elektrik enerjisi üretilebilir. Fotovoltaik sistemlerde verim kayıplarını önlemek için bu sistemlerin düzenli aralıklarla test edilmesi gerekmektedir. Bu çalışmada güneş panellerinden elde edilen termal görüntüler kullanılarak panellerdeki hücre, modül ve panel arızalarının tespiti ele alınmıştır. Çalışma kapsamında dört rotorlu bir insansız hava aracı (drone) tasarlamış ve araca termal bir kamera yerleştirilmiştir. Böylelikle Karabük Üniversitesi binalarının çatısında bulunan güneş panellerinin termal görüntüleri alınmıştır. Elde edilen termal görüntüler kullanılarak hücre hatası, modül hatası ve panel hatasını içeren bir termal veri seti oluşturulmuştur. YOLOv3 derin öğrenme tabanlı evrişimsel sinir ağı, oluşturulan veri seti ile eğitilmiştir. Bu eğitim, gömülü bir yapay zeka bilgi işlem cihazı olan Nvidia Jetson TX2 üzerinde gerçekleştirilmiştir. YOLOv3 ağının eğitiminin tamamlanmasının ardından testlerde bahsedilen arızaların başarıyla tespit edildiği sonucuna ulaşılmıştır.

Anahtar Kelimeler: Fotovoltaik sistem, termografi, derin öğrenme, arıza tespiti ve teşhisi, insansız hava araçları

1. INTRODUCTION

Nowadays, solar energy and its efficient conversion to electrical energy have become one of the most important areas of academic study [1, 2]. Also, the maintenance and repair of photovoltaic systems, which enable us to obtain electrical energy from solar energy, has an increasing importance. In particular, testing a large number of solar panels one by one is very laborious, time consuming and costly. Therefore, the thermography method is used to make the tests of solar panels easier and faster. Thermography is a method used for fault analysis in the energy sector, especially in photovoltaic systems [3]. Thermography measurements show temper.ature differences caused by an external current or light source applied to the PV module [4]. These temperature differences are detected by thermal camera. A thermal camera is basically a video recorder that contains radiometric temperature data in each frame or successive frames [3]. Thermal image of solar panels can be examined through thermal camera and inferences can be made about the condition of solar panels. To make these inferences, thermal images need to be analyzed by experts. Computer-based software needs to be developed to reduce the time to make these inferences. With the software to be developed, faults in thermal images can be detected and diagnosed. The use of artificial intelligence in the detection and diagnosis of these faults increases the success rate. At this point, the deep learning algorithms

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have demonstrated strong capability of self-learning, fault tolerance and adaptability and adopted in many fields, e.g., image classification and speech recognition. The deep learning-based solution can be adopted to analyze the aerial images of PV modules for defect detection and classification [5]. The use of drones during the acquisition of thermal images ensures a fast and error-free result. In this study, thermal images of solar panels are taken by unmanned aerial vehicle and errors on solar panels are detected and diagnosed.

2. LITERATURE REVIEW

Images were obtained with UAV (Unmanned Aerial Vehicle) to detect solar panel faults. DJI brand Inspire 1 model UAV and Zenmuse-xt model thermal camera were used. SSD (Single Shot MultiBox detector) method is used as a deep learning method in detecting faults. As a result of this study, a success rate of 49.11% was obtained [6]. Pierdicca et al. used DCNN (Deep Convolutional Neural Network) as a deep learning method to detect the faults of solar panels in their study. They labeled the pictures showing the anomaly in the panel images and trained the VGG-16 network. The success rate of the trained network was measured as 70%. In the study, Sky Robotic SR-SF6 model UAV and Flir TAU2 model thermal camera were used [7]. Carletti et al. proposed a model-based approach to detect defective solar panels in their study. With this approach, the structural features of the facility were extracted without using color information, and solar panels and hot spots on the panels were determined under variable weather and lighting conditions [8].

In the study by Li et al. developed a system with deep learning-based fault diagnosis to evaluate the status of modules during the inspection of large-scale solar panel fields. A CNN (Convolutional Neural Network) based structure is used as a deep learning method in this developed system. As a result of the study, dust, ghosting, encapsulant, delamination, grid line corrosion, snail traces and yellowing errors are detected. In the study, DJI Matrix 100 model UAV and DJI Zenmuse X3 model camera were used [5]. Wei et al. propose two approaches to detect hot spot and reflective zone faults in solar panels. Classical digital image processing technology mainly uses Hough line transform and Canny operator to detect hotspots. Faster-RCNN uses deep learning method to detect reflector faults. As a result of the study, the classical digital image processing success rate is 89.96%, and the Faster-RCNN deep learning method has a 95.15% success rate [9].

In the study by Akram et al. made automatic detection of solar panel faults in thermal images using isolated deep learning and development model transfer deep learning techniques. This isolated model is trained from scratch using a CNN with an average accuracy of 98.67%. In transfer learning, on the other hand, 99.23% accuracy is obtained by using a basic model [10]. In the study by Diaz et al. propose an automatic fault diagnosis method of solar panels with a thermal camera mounted on the UAV. Two methods, one classical and the other based on deep learning, are used in the detection of solar panel faults. In the first method, the low contrast of thermal images is corrected using several preprocessing techniques. In the second method, R-CNN based neural network is used to describe the solar panel [11]. Herraiz et al. use an R-CNN-based detection structure to detect faults in solar panels using data from a thermal camera placed on the UAV in their study. As a result of the study, hot spots were detected with a success rate of 91.67%. DJI S900 model UAV and WORKSWELL WIRIS model thermal camera are used [12].

Henry et al. propose an autonomous UAV-based thermography system for automatic detection and localization of defective solar panels in a solar panel field. Two cameras, thermal and normal vision cameras, are used in the UAV system. FLIR Vue Pro R model thermal camera was preferred as a thermal camera [13]. Xie et al. developed an algorithm that examines the images taken from the UAV using the Sobel operator and the Canny operator to detect anomalies in the solar panel in their study. In the training of the algorithm, solar panel errors are detected in the images by using CNN as a deep learning method. As a result of the studies, a success rate of 90.91% was achieved [14]. In the study by Venkatesh and Sugumaran, errors in solar panels are detected by CNN deep learning method. The training was carried out using the VGG-16 network. Six panel classifications are considered in the study. These are burn marks, delamination, discoloration, glass breakage, snail marks and robust panel. As a result of the study, a classification success of 95.4% is achieved [15].

3. SYSTEM CONFIGURATION WITH FOUR ROTOR UAV

In this study, a four-rotor UAV is used to obtain the thermal image of the solar panels. Equipped with a thermal camera, the UAV performs autonomous flights on solar panels. The thermal images of the solar panels taken during the flight are recorded on the SD card. The recorded images are uploaded to the Nvidia Jetson TX2 embedded artificial intelligence computer and errors in the thermal images are detected. The block diagram of the designed system is given in Figure 1.

3.1. Four-rotor UAV design

The vehicle's maximum flight weight and flight time were considered while designing the four-rotor UAV. A fuselage design with a calculated maximum flight weight of 2.45 kg and a motor-to-motor diameter of 450 mm was made. This design supports propellers up to 12 inches in size. The designed four-rotor unmanned aerial vehicle is given in Figure 2. The electronic equipment of the four-rotor UAV consists of flight control card, control receiver, telemetry, GPS antenna, power distribution board, power module, ESC, motor, gimbal, and battery. Navio2, which has a high-resolution barometer and two IMU sensors, was chosen as the flight control board.

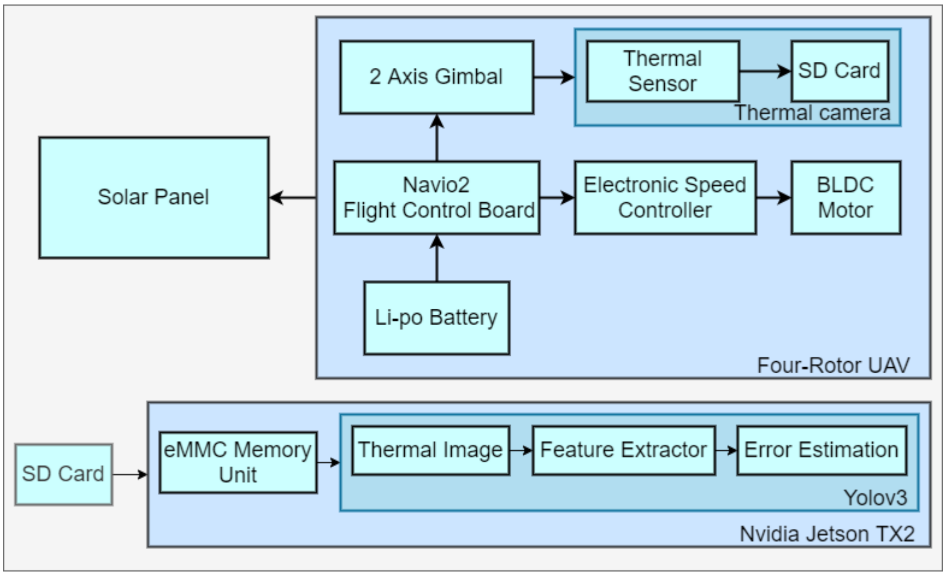


Figure 1. Block diagram of the system

Figure 2. The designed four-rotor unmanned aerial vehicle

At the same time, this card works with Raspberry Pi. X8R produced by FRSKY company was used as control receiver. Tallysman brand Tw4721 model GNSS antenna is used to receive the signals of GPS, GLONAS, Beidou and Galileo satellites. Matek power distribution board is used for power distribution. SunnySky X3108s motors are used as BLDC motors. EMAX BLHeli 25A model ESCs were preferred to adjust the BLDC motor speed, and the Leopard Power 3S 11.1V 6200mAh Li-po battery was preferred as the battery. A maximum flight time of 25 minutes is reached with the mentioned mechanical and electronic hardware structure. The Mission Planner program is used at the ground station to adjust the flight parameter settings of the four-rotor UAV and to display the flight information instantly.

3.2. NVIDIA Jetson TX2 embedded artificial intelligence computer

The Nvidia Jetson TX2 embedded artificial intelligence computer is a powerful computer that allows parallel operation of multiple neural networks such as image classification, object detection and audio processing. Embedded applications are developed for deep learning, IoT, computer imaging and similar studies. Using the Nvidia Jetson TX2 with a GeForce-enabled graphics processor (Graphics Processing Unit - GPU) using the same CUDA cores provides a powerful development environment. In addition, Nvidia Jetson TX2 has a CPU (Central Processing Unit) - GPU heterogeneous architecture [16]. In this architecture, the operating system can be started by the CPU, while the CUDA-compliant GPU can be programmed to speed up complex machine learning tasks. Ubuntu 18.04 operating system runs on Nvidia Jetson TX2 artificial intelligence computer. In this study, the Nvidia Jetson TX2 used to train the YOLOv3 network and detect and diagnose errors in solar panels is given in Figure 3.

Figure 3. Nvidia Jetson TX2 embedded AI computer

The technical specifications of the Nvidia Jetson TX2 embedded AI computer are given in Table 1 [17].

Table 1. The technical specifications of the Nvidia Jetson TX2 embedded AI computer specifications

CPU	2 GHz Arm Cortex-A57 (quad-core)
GPU	256-core Pascal @ 1300 MHz
Memory	8GB 128-bit LPDDR4 @ 1866 MHz
Storage	32GB eMMC 5.1
Ethernet	10/100/1000 Base-T Ethernet

4. DEEP LEARNING BASED FAULT DETECTION AND DIAGNOSIS OF SOLAR PANELS WITH THERMOGRAPHY METHOD

In this study, a four-rotor UAV is used to detect and diagnose faults on solar panels by taking aerial images. Images can be taken to the solar panels via a thermal camera connected to the gimbal placed at the bottom of the vehicle. From these images, a data set for the hot spot errors of the solar panel is created and labeled. These faults are classified as cell, module, and panel faults. YOLOv3 network is used to detect existing errors with deep learning method. With the created data set, the YOLOv3 network is trained, and the network is tested after the training. The thermal images obtained are given to the YOLOv3 network, whose training has been completed, and the faults in the images are detected and diagnosed.

4.1. Thermography method

Thermography is a non-destructive measurement technique that provides fast, non-contact and real-time detection of the characteristics of PV panels. Thermography measurements show temperature differences caused by an external current or light coming into the PV panel. In the measurements made in the dark environment, the faults in the panel are detected by giving external current to the PV panel. Measurements made in a bright environment are usually made under sunlight. Sunlight applied to the PV panel causes an inhomogeneous temperature to increase on the panel.

The regions with an increase in temperature are measured with a thermal camera [18]. Faults in the panel are detected in this way. Thermography measurements should be made at a minimum irradiance value of 700W/m2 and at low wind speed. In addition, the angle between the thermal camera and the PV panel should be 90 degrees for the best view [4].

4.2. Deep Learning Based Image Processing

The primary focus of the deep learning field is to learn appropriate data representations that can be used to reach results. The word “deep” in deep learning refers to the idea of learning the hierarchy of concepts directly from raw data [19]. The basic structure of deep learning, which is a class of machine learning, is based on artificial neural networks. The structure of deep learning is given in Figure 4.

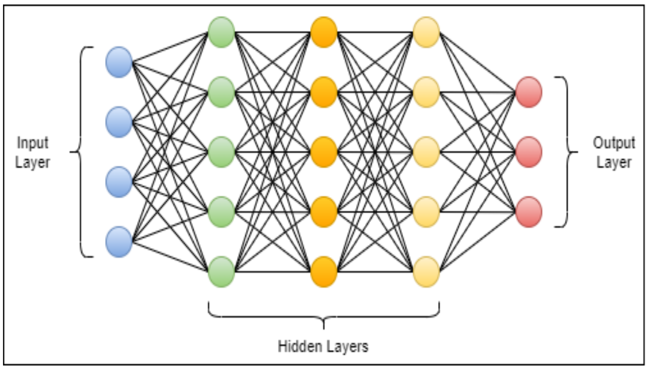


Figure 4. The structure of deep learning

There are input layer, hidden layers, and output layer in deep learning structure. Each sequential layer is used as the output of the previous layer and the input of the next layer. There is a difference between machine learning algorithms and deep learning algorithm [20]. If machine learning makes a wrong prediction, the engineer can intervene and make the necessary adjustments. However, the accuracy of prediction in deep learning is determined by algorithms [21]. Since every problem in which deep learning is applied is not the same, different artificial neural networks are used according to the problem types [22]. These models can be classified as convolutional neural network, Recurrent Neural Network (RNN), Long Short-Term Memory Neural Network (LTSM), Deep Belief Network (DBN) and Deep Auto Encoder.

Within the scope of convolutional neural network, there are algorithms developed for object detection and giving very successful results in object detection [23, 24]. These algorithms: It can be listed as AlexNet, ZFNet, VGGNet, GoogLeNet, Microsoft ResNet, R-CNN, Fast R-CNN, SSD and YOLO.

4.3. YOLOv3 Algorithm

Darknet-53 architecture is used in the YOLOv3 algorithm [25, 26]. Darknet-53, created by combining Darknet-19 and ResNet, consists of 53 layers called convolution, residual, and concatenation. 1x1 and 3x3 filters are used in the convolution layer. Batch normalization and ReLu operations are performed after each of the convolution layers. In the Batch normalization layer, the data is organized by scaling the data coming from the convolution layer and fitting it to a certain range. In the ReLu layer, values less than zero are set to zero. In the Residual layer, the network is prevented from memorizing by using Residual blocks. In the junction layer, a single output is obtained by combining 2 different outputs at the layer input [27]. The YOLOv3 architecture is given in Figure 5.

4.4. Fault detection and diagnosis in thermal images with YOLOv3 network

Thermal images of solar panels are used in the deep learning-based detection and diagnosis of cell fault module fault and panel fault in solar panels. Faults in thermal images are examined with the YOLOv3 network, and panel faults are detected. For the YOLOv3 network to detect faults in the images, a data set containing thermal images should be created. While creating the data set, 11:30 and 15:30 hours, which is the time interval when the sun rays come at a right angle on the solar panel, and the days when the weather is sunny were preferred.

LabelImg, an open-source data labeling program, was used for labeling the data set. The program uses bounding boxes where objects in the images can be marked and annotated [28]. Through this program, images are labeled in a format suitable for the input of the YOLOv3 network. The screenshot of the program named LabelImg is given in Figure 7.

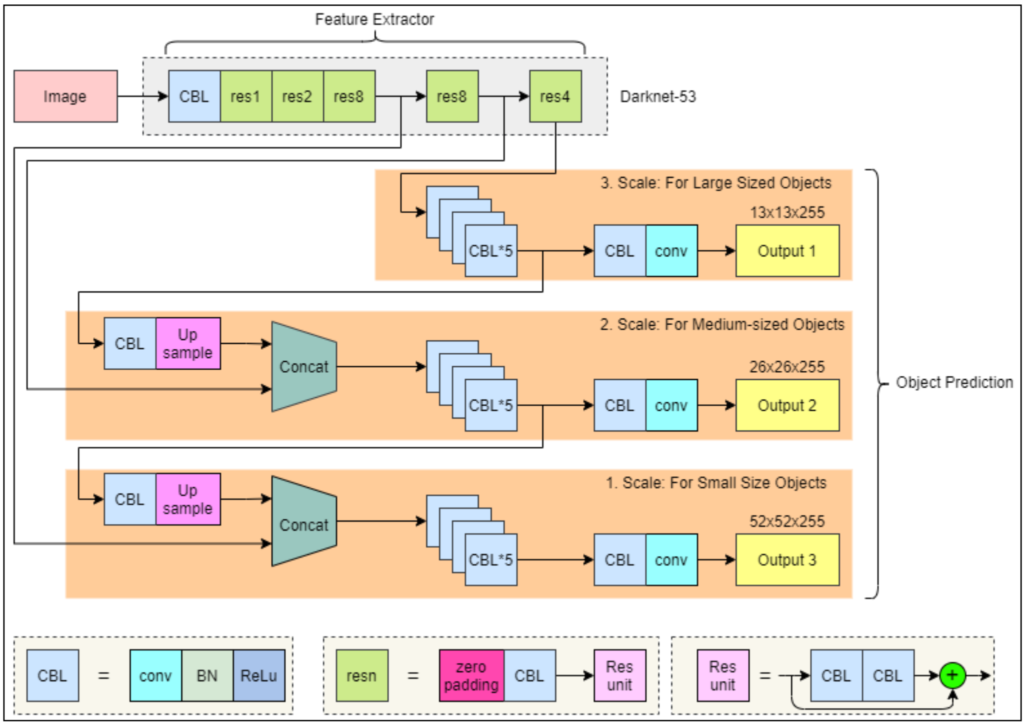


Figure 5. YOLOv3 architecture

The thermal images of the faults obtained with the FLIR DUOR thermal camera are given in Figure 6. For the YOLOv3 network to identify the images in the dataset, the images used in the dataset must be classified. This classification process is called labeling.

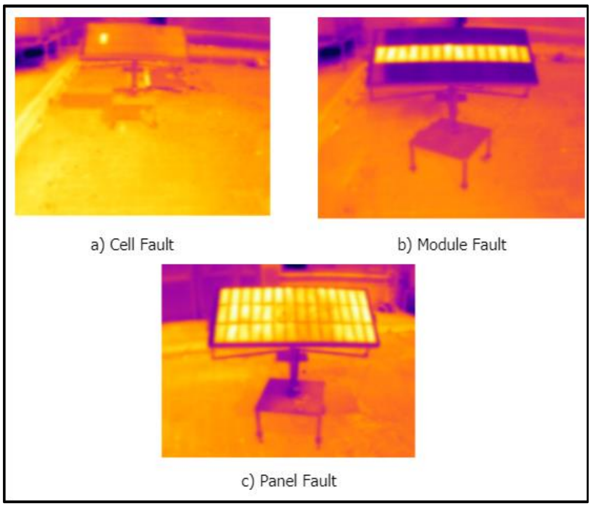


Figure 6. Cell fault, module fault and panel fault obtained with thermal camera.

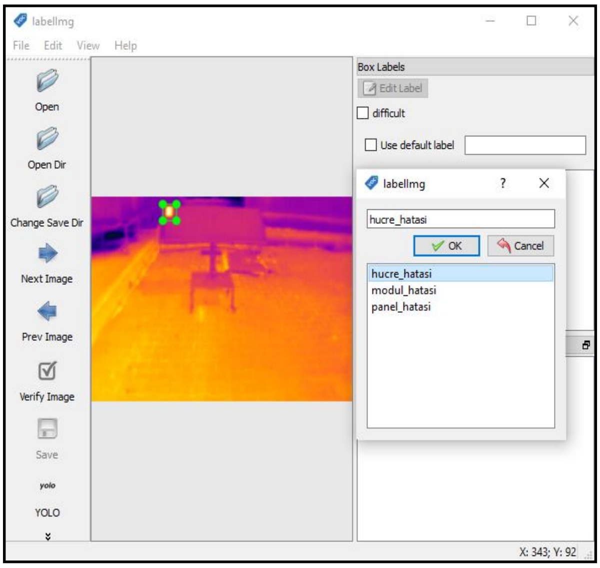


Figure 7. LabelImg data labeling program

With this program, the fault images in the data set are marked with pixels and the faults of these labeled faults are written. After the labeling is finished, the training process of the YOLOv3 network is started. After the data set labeling process, the training process of the YOLOv3 network is performed. The training of the network was done on the Nvidia Jetson TX2 artificial intelligence computer. Deep learning architectures training set needs a validation dataset to validate the training and a test dataset to test the created model. 162 images were used to train the YOLOv3 network on the Nvidia Jetson TX2 artificial intelligence computer. 144 of these images are for training and 18 for testing purposes. 72 of the images used for training consist of cell faults, 54 of them module faults and 36 of them panel faults. The images used in the training and validation dataset are taken from 162 images in the thermal dataset. The loss graph that occurs according to epochs during the training is given in Figure 8.

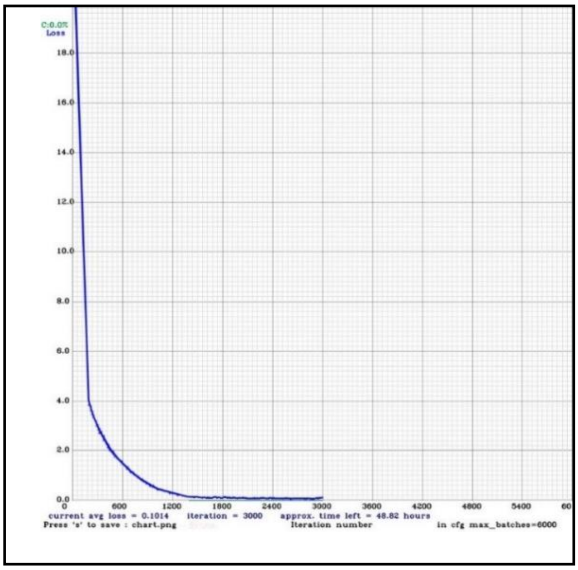


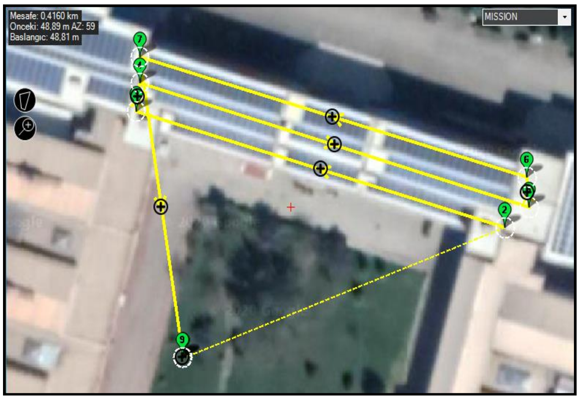
Figure 8. Training loss graph

The y-axis of this graph shows the loss rate, and the x-axis shows the training step. According to the graph, the loss rate, which is more than 18% at the beginning of the training, decreases to 0.1014% at the 3000th step of the training. In deep learning architectures, the loss rate should be less than 1% to understand the completion of a network's training. Therefore, the training of the network is completed in 3000 steps. The duration of this training is approximately 96 hours. During the training of the network, weight files are recorded every 100 steps up to the first 1000 steps. After 1000 steps, weight files are saved every 1000 steps.

5. EXPERIMENTAL RESULTS

Test flights were performed on solar panels with the developed four-rotor unmanned aerial vehicle. With the saved data, the YOLOv3 network was trained, and a fault detection application was performed. Experiments within the scope of this study were carried out on solar panels in Karabuk University. The solar panels on the roof of Karabuk University buildings and the autonomous flight trajectory created for the fault detection test is given in Figure 9.

(a)



(b)

Figure 9. The solar panels on the roof of Karabuk University buildings and the autonomous flight trajectory created for the fault detection

Experimental equipment consisting of four-rotor UAV, thermal camera and Nvidia Jetson TX2 artificial intelligence computer is given in Figure 10.

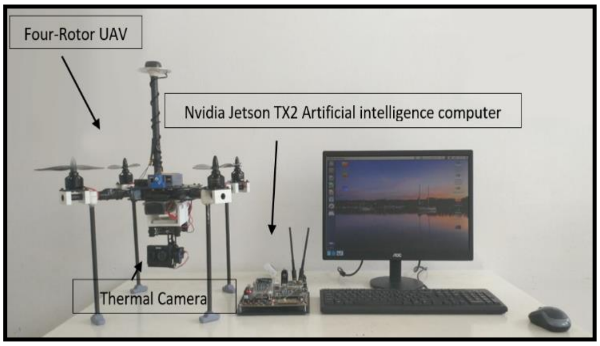
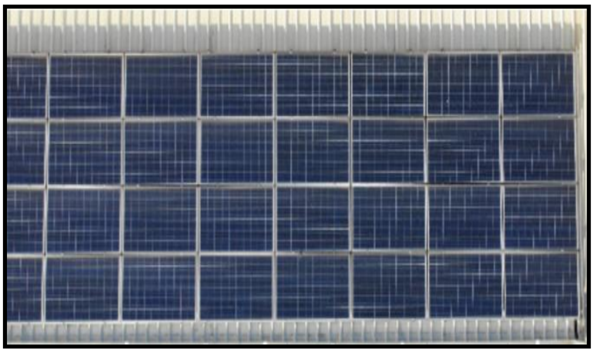


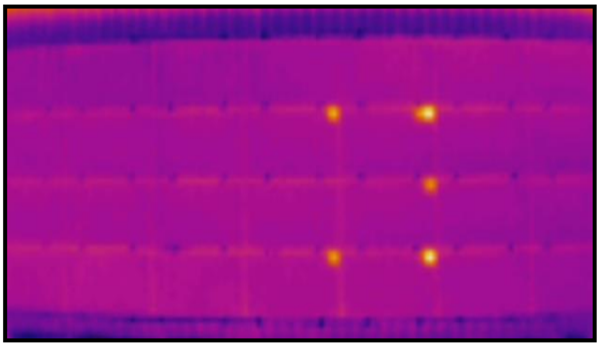
Figure 10. Equipment used in experiments

Autonomous flight was performed on the solar panels with the UAV with thermal camera and the thermal images of the panels were saved on the SD card. The images saved on the SD card were uploaded to the Nvidia Jetson TX2 artificial intelligence computer and faults in the thermal images were detected.

Experimental studies were carried out on sunny days in February and March. On days when the average air temperature is 10-15 °C, the time interval between 11:30 and 15:30 was preferred. The flight altitude was determined as 35m, the height at which the thermal images of the solar panels are the clearest, and a total of 18 flights were carried out. The average duration of autonomous flights was measured as 5 minutes and 15 seconds. The visible and thermal images of the solar panel obtained during autonomous flights are given in Figure 11.



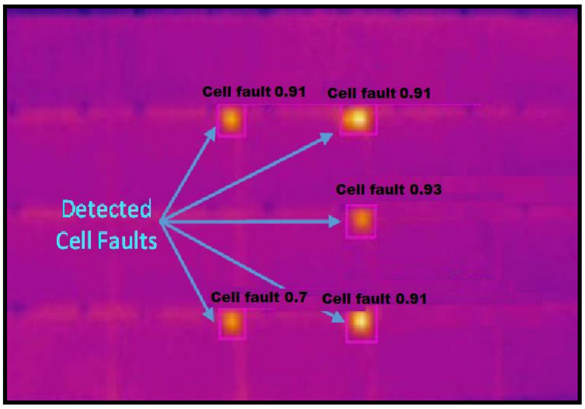
(a)



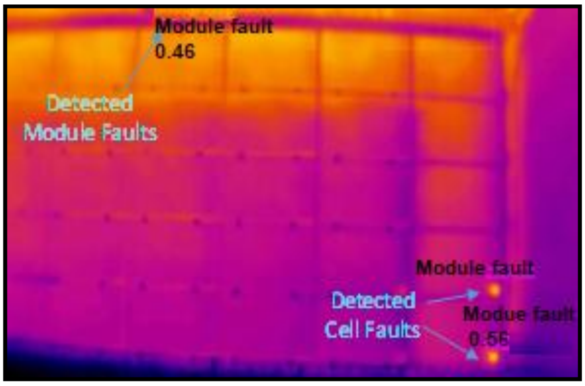
(b)

Figure 11. (a) Visible image of the solar panel; (b) thermal image of the solar panel

Images of the solar panel faults that are detected and diagnosed by applying the images obtained during the autonomous flight to the network and then labeled are given in Figure 12.



(a)



(b)

Figure 12. Images of the solar panel faults that are detected and diagnosed

The comparison of actual and estimated fault values is given in Table 2. In this table, the sum of the values in the row for each fault is the actual number of faults for that fault; the sum of the values in the column for each fault gives the number of predictions for that fault. According to this table, there are 28 images with actual cell fault. All predictions based on these images consist of cell fault. The estimated number of images as cell fault is 29. In one of these images, the panel fault is detected as a cell fault. There are 9 images as a module fault.

Table2. Comparison of actual and estimated fault values

Faults	**Cell fault**	28	0	1
	Module fault	0	8	1
	Panel fault	1	1	5
		Cell fault	**Module fault**	**Panel fault**
		Estimated faults		

Various terms are used to describe Table 2 and to find the performance values of the Yolov3 network. These are accuracy, precision, sensitivity and F1 score. The expressions positive true (TP), positive false (FP), negative true (TN), and negative false (FN) are used to calculate these terms. Positive true expression means that there is a fault in the image and this fault is found to be true according to the prediction result. Positive false means that there is no fault in the image, but an error is detected according to the prediction result. Negative true means that there is no fault in the image and no fault is estimated. Negative false means that there is an error in the image, but there is no error in the prediction result. The terms accuracy, precision, sensitivity and F1 score are used when calculating the success rate. The truth expression of these terms is calculated by dividing the sum of positive true and positive false expressions by all expressions. Equation 1 gives the equation of the truth term.

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

The precision term is calculated by dividing the positive true by the sum of the positive true and positive false expressions. Equation 2 gives the equation of the precision term.

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

The sensitivity term is calculated by dividing the positive true expression by the sum of the positive true and negative false expressions. Equation 3 gives the equation of the sensitivity term.

$$Sensitivity = \frac{TP}{TP+FN} \quad (3)$$

The F1 score term is calculated by taking the harmonic average of precision and sensitivity. The equation of the F1 score term is given in Equation 4.

$$F1\ score = 2\ x\ \frac{Precision\ x\ Sensitivity}{Precision + Sensitivity} \quad (4)$$

The performance values of Yolov3 network made according to the above equations are given in Table 3.

Table 3. Performance values of Yolov3 network

	Cell fault	Module fault	Panel fault
Accuracy	0,97	0,95	0,93
Precision	0,96	0,88	0,83
Sensitivity	1	0,89	0,71
F1 score	0,98	0,89	0,77

The data in the column of the table represent the faults, and the data in the row represent the performance values related to the faults. Detection and diagnosis of cell fault was done with 97% accuracy, 96% precision and 100% sensitivity. The F1 score of cell fault was found to be 98%. Detection and diagnosis of module fault was made with 95% accuracy, 88% precision and 89% sensitivity. The F1 score of the module fault was found to be 89%. Detection and diagnosis of panel fault were made with 93% accuracy, 83% precision and 71% sensitivity. The F1 score of the panel fault was found to be 77% [29].

6. CONCLUSION

In this study, the detection and diagnosis of cell, module and panel faults in solar panels were successfully carried out with a deep learning approach using thermographic images. The developed UAV system was tested on the solar panels placed in the Faculty of Technology building at Karabuk University. Deep learning based Yolov3 convolutional neural network is used in the detection and diagnosis of errors by using the images obtained with the thermal camera placed on the UAV. This neural network is preferred because it works at the same time but with higher accuracy than other deep learning-based convolutional neural networks. The images taken with the thermal camera were labeled as cell, module and panel faults, and a separate data set was created for each. Yolov3 network is trained with this thermal dataset. The training was carried out on the Nvidia Jetson TX2 device, an embedded artificial intelligence computer. The training of the Yolov3 convolutional network was completed in 3000 steps with 162 images. In the experiments conducted after the completion of the training, 97% accuracy in the detection and diagnosis of cell fault, 95% in the detection and diagnosis of module fault, and 93% in the detection and diagnosis of panel fault was determined.

As a result of the tests with thermal images, it is seen that the accuracy rates obtained in the Yolov3 network are sufficient. Retraining the Yolov3 network with thermal images from different types of solar panels will increase the accuracy rate. Also, using another thermal camera with higher resolution will make it easier to detect faults in images.

In future studies, a comparison between these architectures can be made using different deep learning architectures in fault detection and diagnosis with thermal images of solar panels. In addition, the thermal images obtained by integrating the Nvidia Jetson TX2 artificial intelligence computer into the quadrotor UAV can be processed instantly on the UAV and faulty solar panel positions can be sent to the user instantly. And in this way, the error detection and diagnosis process can be reduced.

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DECLERATION OF ETHICAL STANDARTS

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

Barış KAYCI: Performed the experiments, analyzed the results, and wrote the manuscript.

Batıkan Erdem DEMİR: Conceived the study, analyzed the results, and wrote the manuscript.

Funda DEMİR: Analyzed the results, did the literature research, and wrote the manuscript.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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