©2025 Published in 11th International Symposium on Intelligent Technologies in
Engineering and Science 16-18 May 2025 (ISITES2025 Diyarbakır - Turkey)

Deep Learning Based Fault Detection in Solar Panels Using Unmanned Aerial Vehicle with Thermal Camera

[1]Enes Buğra ACAR *[2]Bayram KÖSE,
[1]Gazi Mustafa Kemal, Kaynaklar Cd., 35665 Menemen, İzmir, Turkiye
*[2]İzmir Bakırçay University, Faculty of Engineering-Architecture,Electrical and Electronics Engineering, İzmir, Turkiye

Abstract

Solar energy is one of the most vital energy sources for human life. Although the production and installation of photovoltaic panels is simpler and more economical compared to other energy generation technologies, it can lead to significant cost increases if failures are not addressed in a timely manner. Therefore, early detection of faults and rapid response play a critical role in maintaining system performance and minimizing potential risks. Therefore, in this study, deep learning-based fault detection is performed using an unmanned aerial vehicle (UAV) with a thermal camera. YOLOV7 (You Look Only Once) algorithm, one of the current deep learning algorithms published in 2022, was used for automatic fault detection. In the study, the images taken with the thermal camera were processed and systematically analyzed with the YOLO algorithm model used in the training phase. In the training phase of the algorithm, a data set consisting of a total of 325 thermal images was used. The training consisted of 120 epochs and was completed in approximately 19 hours. As a result of the tests, it was observed that the developed system was able to detect faults with an accuracy of 0.91. This approach is considered as an important innovation in industrial maintenance processes.

Key words: Solar Panel, UAV, Deep Learning, YOLO Algorithm, Renewable Energy

1. Introduction

Today, sustainability and environmental impacts are of great importance in the energy sector. Climate change and environmental problems caused by the use of fossil fuels have made it mandatory to research and use alternative energy sources worldwide. With the advancement of technology, interest in renewable energy sources has increased considerably. Solar energy is one of these sources, which has many benefits such as reducing carbon emissions, ensuring sustainability and eliminating foreign dependency. Panels that produce energy from sunlight can now be easily installed in our homes and even in our gardens, as well as in factories and solar fields. In this context, renewable energy sources such as solar panels have great potential. A solar panel is a technology that converts sunlight into electricity. The fact that the sun is an unlimited and clean energy source is one of the biggest advantages that distinguishes the solar panel from other energy sources.

Today, an effective monitoring and detection system is required to ensure the healthy functioning of industrial plants, power plants, natural resource areas and many similar infrastructures. Failures, pollution due to various reasons, and localized problems that may occur in these facilities can cause

*Corresponding author: Address: İzmir Bakırçay University, Faculty of Engineering-Architecture, Electrical and Electronics Engineering TURKEY. E-mail address: bayram.kose@bakircay.edu.tr, Phone: +90 505 695 2179

serious economic losses and environmental damages[1]. Therefore, early detection and rapid response to these problems is of great importance.

In recent years, the unmanned aerial vehicle (UAV) technology has experienced a groundbreaking development in the field of industrial monitoring and detection. Especially with the integration of thermal and normal cameras, real-time and comprehensive data collection through UAVs has become possible[2]. This data provides easy access to areas that are difficult to reach with traditional methods and can quickly scan a large surface area.

The novelty of fault detection with the UAV is the use of YoloV7, a deep learning algorithm, which was released in 2022, in the UAV with thermal camera. This algorithm, which is faster than its previous versions, is expected to contribute to the literature by combining with today's UAV technology, rather than reaching conclusions only by image processing from thermal image data sets in the literature. This method can be used not only in solar panels but also in areas such as fault detection of windmills [3].

The structure of the article is based on a literature review after the Introduction. In the third section, information on Materials and Methods is given. In the fourth section, under the title of Application and Analysis, calculation results and findings are shown. In the fifth section, general evaluation results are explained.

1.1. Literature Review

Failures in solar panels reduce energy efficiency and can cause great damage to solar panels. In order to solve this problem in solar panels, defective and dirty panels should be detected and maintained. Various academic studies have been conducted internationally with the methods used in the detection of defective solar panels.

For example, in 2013, Higuchi and Babasaki compared several methods to identify failed panels and found that UAV detection was the most efficient. They showed thermographic images captured by the drone and explained various panel failures. An investigation with deep learning revealed that single-shot detection (SSD) is an effective detection method. Using 4 MW solar power plant data, they conducted tests with the SSD model and achieved an average accuracy score of 49.11%[1].

In 2018, Pierdicca et al. presented a new approach with DCNNs to predict the degradation of PV cells. Experiments on a collected dataset, the “Photovoltaic Images Dataset”, showed the degradation problem and provided a comprehensive evaluation of the method presented in the research. The success rate of the trained network was 70%.In the study, an aircraft with the brand name Sky Robotic and model SR-SF6 was used. The thermal camera was a Flir camera and TAU2 camera [4].

In 2019, Wei et al. proposed two different approaches to detect hot spots in the infrared image of PV modules. Classical digital image processing technology (DDI) usually detects hot spots using Hough line transform and Canny operator. The deep learning model is based on Faster-RCNN and transfer learning and has shown better performance with more computational resources. At the end of the study, the success rate of KDGI was 89.96% and the success rate of Faster-RCNN was 95.15%[5].

Kaycı's study in 2021 focused on the detection of cell, module and panel defects in solar panels. In this study, a four-engine unmanned aerial vehicle (UAV) was designed and a thermal camera was placed on it. A data set was created by taking thermal images of solar panels on the roof of Karabük University Faculty of Technology building. This dataset is categorized into three classes: cell failure, module failure and panel failure. Then, this thermal data set was trained with the Yolov3 algorithm. The results obtained at the end of the training showed that cell faults were detected with 98% accuracy, module faults with 95% accuracy and panel faults with 93% accuracy [2].

In Akram et al.'s study, automatic detection of solar panel defects in thermal images was realized using isolated deep learning and transfer learning techniques. This isolated model was trained from scratch using a CNN and achieved an average accuracy of 98.67%. On the other hand, in transfer learning, 99.23% accuracy was achieved using a basic model [6].

In a study by Venkatesh and Sugumaran, faults in solar panels were detected using CNN (Convolutional Neural Network) deep learning method. VGG-16 network structure was preferred in the training phase. Six different panel types were classified: burn marks, delamination, discoloration, glass breakage, snail marks and intact panels. This study achieved successful results with an accuracy rate of 95.4% [7].

In their study, Herraiz et al. used an R-CNN-based detection structure to detect defects in solar panels using data obtained from a thermal camera mounted on a UAV. As a result of the study, hot spots were detected with a 91.67% success rate. The brand of the UAV was DJI model S900 and the thermal camera model WORKSWELL WIRIS was used [8].

Carletti et al. proposed a model-based method for detecting faulty solar panels. In this method, the structural features of the facility are analyzed without using color information. In addition, solar panels and hot spots on them were successfully detected under different weather and lighting conditions[9].

In his research on the performance and power evaluation of photovoltaic solar panels, Altaee studied the electronic control unit plant. The study succeeded in achieving high efficiency at low cost in terms of the suitability of the system[10].

In Kawamoto and Shibata's research, a cleaning system was developed to remove dust and dirt accumulated on photovoltaic panels, resulting in a significant increase in the amount of energy produced. This system improved the production quality by 90%. An electrostatic cleaning device was used to clean the dust accumulated on the solar panel surface. This device removes 90% of the sand adhered to the glass surface by applying single-phase high voltage to electrons through parallel wires placed inside the panel glass coating. Moreover, the energy consumption of the developed system is very low [11].

In Saidan et al.'s research, an investigation was carried out on the effect of dust and pollution on photovoltaic cells on photovoltaic panels and the energy losses caused by this effect. In order to measure these energy losses, an experimental environment was created and measurements were made in monthly, weekly and daily periods. The production losses on photovoltaic panels exposed to dust and dirt within the scope of the experiment were measured as 18.74% monthly, 11.8% weekly and 6.24% daily [12].

F. Meja et al. recorded the production losses of an 84 kW power plant due to pollution from the natural environment. They used data on rainfall and insolation from a weather observation station located in the vicinity of the solar panel. They observed a 0.21% decrease in production efficiency on one day due to pollution. During a 108-day rain-free period in the summer, yields increased from 5.6% to 7.2%. When the rains started again, the yield decreased again to 7.1% [13].

In Xie et al.'s study, an algorithm was developed using Sobel and Canny operators to analyze images from a UAV and detect anomalies in solar panels. In the training of the algorithm, CNN was used as a deep learning method and defects in the panels were detected. As a result of the study, the success rate was found to be 90.91%[14].

Diaz et al. proposed automatic panel fault detection using a thermal camera integrated into a UAV. Two methods based on classical and deep learning were used to detect defective panels. 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 identify the panel [15].

In his study, Yücel used deep learning to detect damage from EL images of 6528 monocrystalline and polycrystalline solar panel cells. The images were classified as intact, broken and cracked and analyzed with CNN models such as Xception, Vgg16, Vgg19, Resnet50, DenseNet201 and MobileNet. The models obtained successful results by evaluating monocrystalline and polycrystalline cells separately[16].

In Selim's study, the pollution level of solar panels was classified using NasnetLarge and MobileNet algorithms. NasnetLarge worked with 97% accuracy rate and MobileNet worked with 98% accuracy rate. The study aims to quickly and effectively determine the pollution status of solar panels installed in large areas [17].

The aim of Hale's study is to identify the types of faults in solar panel plants in Turkey and provide investors and businesses with rapid analysis to improve energy production. Fault detection was performed in the field using infrared thermal detection and thermal image processing. In the analysis of a 600-kW solar power system in Turkey, it was found that connection faults caused the panels to stop working. Elimination of these faults resulted in a 0.16% improvement in energy production [18].

In Yunus Emre's study, electricity generation is analyzed using daily and hourly data sets of 1 MW capacity solar power plants (Power Plant_A, Power Plant_B, Power Plant_C, Power Plant_D) located in Çumra, Tuzlukçu and Yunak districts of Konya. During the analysis, the long short-term memory (LSTM) model was preferred as a deep learning technique and the results of this model were compared with the seasonal autoregressive moving average (SARIMA) model. Based on five different error measurement criteria (MSE, RMSE, NMSE, MAE, MAPE), it is observed that the LSTM model is generally more consistent with the real data than the SARIMA model [19].

Safiye's study aims at automatic detection of lesions and caries in dental X-rays using a deep learning algorithm based on YOLOv7. Using 400 panoramic dental X-ray images marked by an expert dentist, lesion and caries regions were identified. The images were converted to YOLOv7 format on the Roboflow platform and the model was trained with this data. The model achieved high accuracy in lesion and caries detection on dental X-rays, with a mAP value of 38%. These results can improve diagnostic consistency and reduce interpretation errors [20].

Oluwaseyi developed a system for vehicle detection using the YOLO algorithm. The YOLOv7 model was trained with various deep learning algorithms and tested on real-time traffic surveillance videos in different weather conditions (rainy, sunny, night, snowy and foggy) in Lagos and Istanbul. The number of vehicles was determined and automatically stored in a database using Python. In addition, line graphs were generated with Matlab to monitor the growth rate of congestion. The results show that there is no significant difference between the two cities, but the model underperforms in foggy weather [21].

Batuhan and Ali's study aims to run the YOLOv7 model on the server for object detection on smart mobile devices without using a graphics processing unit. The YOLOv7 algorithm was successfully implemented on devices with iOS operating system. Images taken with mobile devices or images in the gallery were transferred to the server for fast and accurate object detection [22].

Sümeyye et al. investigated the effectiveness of YOLO algorithms for hotspot detection in PV modules in solar power plants. The performances of YOLOv5, YOLOv6, YOLOv7 and YOLOv8 algorithms were compared and the best model was determined. The 100 images obtained from the UAV were used as 80% training set and 20% test set. According to the results, YOLOv8 algorithm outperformed the others with 88.7% specificity, 80.5% sensitivity and 83.8% mAP. The dataset is taken from real solar panels and the results are in accordance with real-world conditions. The study emphasizes the importance of object detection algorithms in solar power plants [23].

2. Materials and Method

2.1. Data Set

The dataset to be used in the algorithm consists of a total of 325 temperature thermal images, 295 for training and 30 for testing. The images were taken from solar panels located in the car parking lot of Izmir Bakırçay University. The IR resolution of the images is 256X192. The images were taken between 13-00 and 15.30 hours when the sun was at its peak. Thus, the quality of the data was ensured. Although the images were generally taken as a single panel, there are also group panels in some photographs. In order to increase the data set, the data set was duplicated by using the mirroring method in most of the defective panels.

2.2. Material

In the application, a ready-made UAV was purchased and the thermal camera module was integrated. A small electronic system was installed for the thermal camera. In the installed system, UNI-T Uti721M model thermal camera and Jetson Nano single card computer were used to integrate it. At the same time, Jetson Nano, which contains deep learning, will instantly save the thermal images it receives while the UAV is in the air. When the mission is completed and the UAV lands on the ground, the memorized images will be inserted into the YoloV7 network, which is a deep learning method, and error detection processes will be initiated. A comprehensive block diagram of the system used is given in Figure-1.

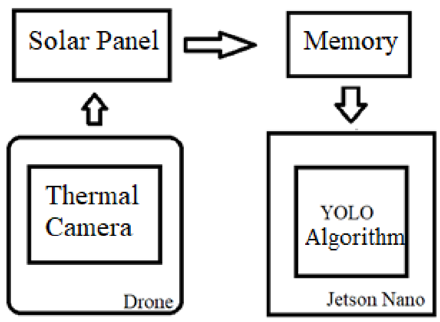

Figure 1. Block Diagram of the System

Jetson Nano: The NVIDIA Jetson Nano Developer Kit provides a powerful platform capable of computing artificial intelligence algorithms. This kit can be powered via micro-USB and offers a wide range of I/O options, including GPIO and CSI. At the same time, it provides energy efficiency by attracting attention with its low energy consumption. Jetson Nano is supported by NVIDIA JetPack software, which includes the board support package (BSP), Linux operating system, NVIDIA CUDA®, cuDNN and TensorRT™ software libraries required for deep learning, image processing and GPU programming. Technical specifications are shown in Figure-2. [24].

GPU	NVIDIA MAXWELL, 128 CUDA CORE
CPU	4-CORE ARM A57 @ 1.43 Ghz
MEMORY	4 GB 64 BIT LPDDR4 | 25.6 GB/s
STORAGE	MicroSD
VIDEO	4K @ 30 | 4X1080p @ 30 | 9x720 @ 30 ENCODER 4K @ 60 | 2X4K @ 30 | 8x1080 @ 30| 18x720p @ 30 DECODER
CAMERA	1x MIPI CSI-2 DPHY Lanes
CONNECTION	GIGABIT ETHERNET, M.2 KEY E
SCREEN	HDMI 2.0 and eDP 1.4
USB	4x USB 3.0 USB 2.0 Micro-B
OTHER	GPIO, I2C, SPI, UART
DIMENSIONS	100 mm x 80 mm x 29 mm

Figure 2. Jatson Nano Technical Specifications [24].

Figure 3. UNI-T UTI720M [25]

Thermal Camera: The technical specifications of the thermal camera to be used are as follows: IR resolution is 256×192 and the temperature measurement range is between -20℃ and 200℃ (-4℉ to 392℉). The device has an automatic alarm system for high and low temperatures and can automatically track hot spot/cold spot tracking. Screen analysis features include 3 points, 3 lines and 3 rectangles. Image capture, video recording and 7 different colour palettes (White hot, Black hot, Red hot, Iron Spring, Lava, Rainbow, Rainbow HC) are available. The camera works with the Android operating system via USB Type-C connection and comes with a 1 metre long extension cable. It is also resistant to a drop from a height of 1 metre. The visualisation of the camera is presented in Figure-3. [25].

Unmanned Aerial Vehicle (UAV): The unmanned aerial vehicle used in the study is the DJI Mavic 3T Enterprise model. This model draws attention with its compact and portable structure. It offers a maximum flight time of 45 minutes and has a wide-angle camera with a 4/3 CMOS sensor. It also features a 56x hybrid zoom and a 640×512-pixel resolution thermal camera (available for Mavic 3T). Equipped with the DJI O3 Enterprise Transmission system, it provides centimetre-precise positioning thanks to RTK technology [26].

2.3. Machine Learning

Machine Learning (ML) is an important branch of artificial intelligence based on the ability of computer systems to learn from data. This set of algorithms and techniques enables computers to analyse data, recognise patterns and predict future events. Essentially, machine learning uses data analysis and mathematical modelling techniques to give computers the ability to perform a specific task. Machine learning is different from traditional programming, which is used to perform a specific task. In traditional programming, software developers create explicit rules and instructions to perform a specific task. But in machine learning, an algorithm learns how to perform a specific task by analysing data [27].

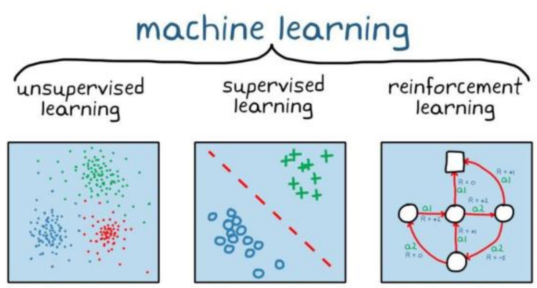

Figure 4. Categories of Machine Learning

Machine learning is generally divided into three main categories as shown in Figure-4:

Supervised Learning: In supervised learning, the algorithm learns the relationships between data using training data. Using these relationships, it gains the ability to classify or predict new data. For example, it can be used to classify emails as spam or not spam. The visualisation of the working principle of the Allgorithm is given in Figure-5. [27].

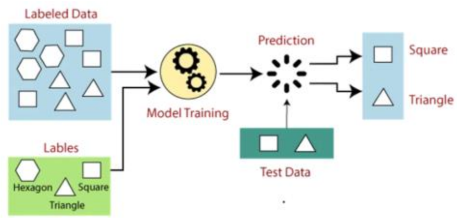

Figure 5. Working Principle of Supervised Learning [27].

Unsupervised Learning: Unsupervised learning is used to recognise patterns or groups in a data set. The algorithm looks at the data, recognises the relationships between the data by itself and can classify the data into groups. This type of learning is especially used for data discovery and segmentation. An example is given in Figure-6. [28]

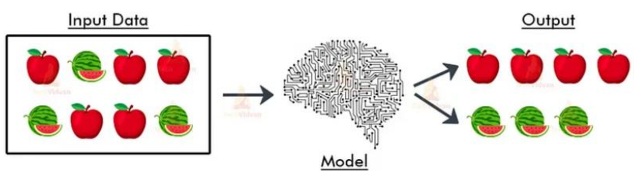

Figure 6. Unsupervised Learning Example [27].

Reinforcement Learning: In reinforcement learning, an agent (e.g., an autonomous vehicle or an AI game character) tries to fulfil a specific task in a given environment. The agent interacts with its environment and receives rewards or punishments as a result of certain actions. Based on these rewards, the agent learns the best action and tries to fulfil the task. The visualisation of the working principle is given in Figure-7. [28].

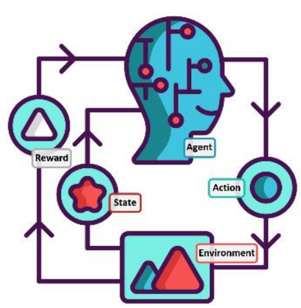

Figure 7. Reinforcement Learning Working Principle [29].

Machine learning is used in many application areas, such as natural language processing, image recognition, voice analysis, healthcare, finance, game development, self-driving cars and many more. Machine learning has great potential thanks to its capacity to analyse big data and solve complex problems, and is expected to play an even more important role in the future.

2.4. Deep Learning

Deep learning (DL) is a technology and learning approach that has attracted much attention and significant development as a sub-branch of artificial intelligence (AI). Deep learning greatly improves data analysis and pattern recognition capabilities by using multi-layered and complex mathematical structures called artificial neural networks. Deep learning is fundamentally based on the ability to process large data sets, extract meaning from data and solve complex problems. A single neural network model consists of many layers, and each layer processes a specific type of information. The interactions between these layers provide the large learning capacity of deep learning [17].

Multilayer Structures, Deep learning models contain many layers. Each layer processes different features of the data. This provides the ability to recognise more complex and abstract patterns. Sequential Learning involves the use of sequential steps to process the data and improve the results. At each step, the model is compared with the error and the error is tried to be reduced. In this way, the model continues to learn and understand the data better. Big Data, Deep learning works effectively on large data sets. More data helps the model learn better and make more accurate predictions. Autonomous Learning, Deep learning models have the ability to learn without the need for human intervention. As they are exposed to data, they continue to evolve on their own. Various Applications; Deep learning is used in natural language processing, image recognition, game development, medical diagnostics, automation, driverless vehicles and many more. Therefore, deep learning is a versatile learning approach [16].

Deep learning has great potential in many industries and sectors thanks to its ability to solve complex problems and analyse large data sets. It is considered one of the most important advances in the field of artificial intelligence and is expected to grow and become more widespread in the future. Deep learning has opened new horizons in the field of machine learning and enabled the development of more intelligent and autonomous systems [30].

Artificial Neural Networks (ANN) form the basis of the field of deep learning. These networks are mathematical models inspired by biological nervous systems. While Convolutional Neural Networks (CNN) are used for image processing and analyzing sequential data, Long Short-Term Memory (LSTM) networks are used in tasks such as sequential data analysis and language processing. A simple ANN example is given in Figure-8. [8].

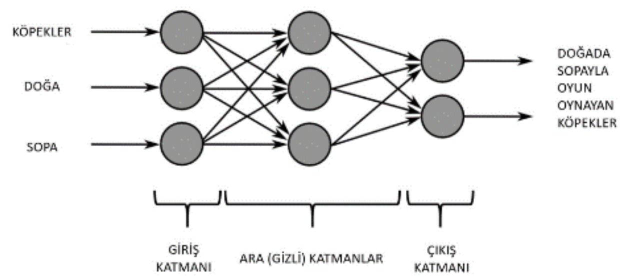

Figure 8. Example Artificial Neural Network

Convolutional Neural Networks (CNNs) are used especially in image recognition and processing tasks. They are effective for the detection of patterns and features in image data. CNNs consist of convolutional layers, pooling layers and fully connected layers.

YOLO (You Only Look Once) is an effective deep learning algorithm developed for object detection. YOLO divides the image into small parts and analyses the image in a single pass and identifies, classifies and locates objects in boxes as in Figure-9. Thanks to this feature, it can be used in real-time applications. In addition, it analyses objects in detail by making multiple structureless predictions and can detect them with high precision [2].

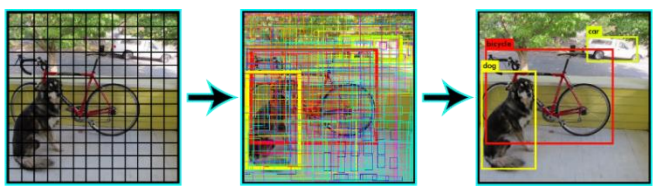

Figure 9. Yolo Algorithm Working Principle [31].

While the advantages of YOLO include fast processing and multi-object detection, it has some weaknesses in detecting small objects and object classification accuracy. YOLO is used in many application areas such as driverless vehicles, security cameras, object tracking and recognition, and represents a significant advance in the field of object detection. The architecture of the algorithm is shown in Figure-10.

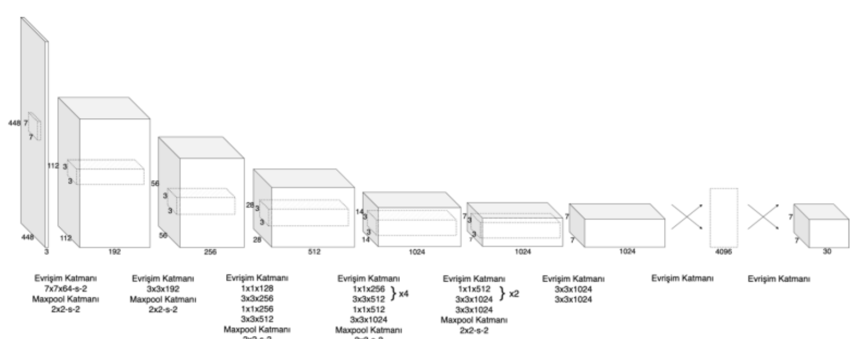

Figure 10. YOLO Architecture [31]

YoloV7, one of the Yolo algorithms, is an object detection and classification algorithm. YOLOv7 is an improved version of its previous versions. It is a convolutional neural network (CNN) model used to detect and classify objects in images. The algorithm performs the detection and classification of objects by analyzing an image once. This provides faster results than some other methods and can be used in real-time applications. YOLOv7 includes several improvements over previous versions of YOLO. These improvements may include better object detection accuracy, faster processing speed and better scalability. In addition, transfer learning methods can be used, which provide more learning capabilities so that the model can be adapted to a more general dataset. YOLOv7 can be used in many areas such as computer vision, object detection and autonomous vehicles. It provides an effective solution in many application scenarios where objects need to be detected, tracked, classified and recognised. The architecture of YoloV7 is given in Figure-11. [17]

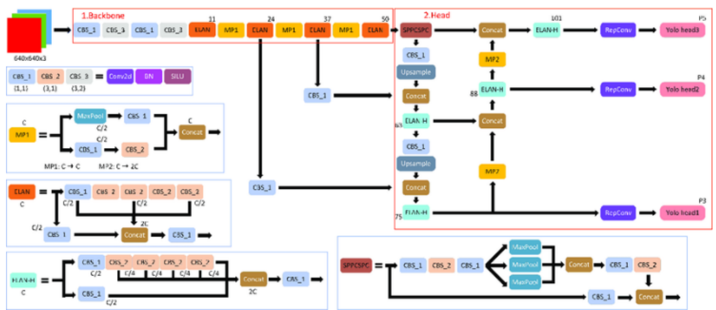

Figure 10. YoloV7 Architect [32]

3. Application and Analysis

The dataset created from the thermal images was labelled and errors were classified before being inserted into the YoloV7 network. LabelImg programme was used for labelling. Due to the lack of cameras and solar panels to be used in the data set, 1 class was determined as shown in Figure-12 and labelled as Faulty. The identified faults were labelled through the LabelImg program as shown in Figure-13. This labelling will help the model during learning.

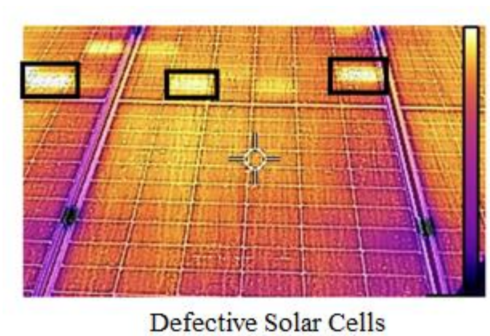

Figure 12. Error Detections

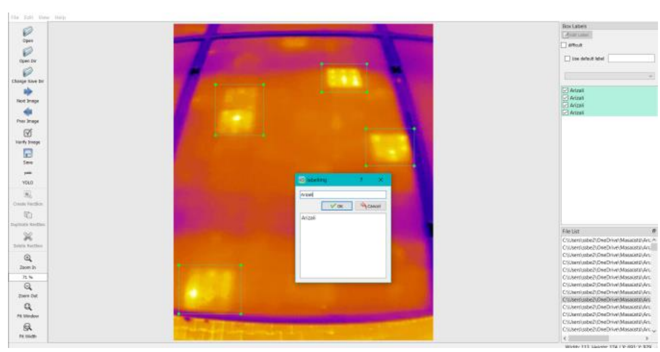

Figure 13. Labeling of Dataset

In the programme used, the Defect images in the dataset are labelled with boxes and these labelled defects are written as Defective. After the labelling process is finished, the training process of the YOLOv7 network is started. The training process of the network was carried out on the Jetson Nano computing card. In order to train and test the model of deep learning algorithms, a part of the data set should be allocated to training and another part to testing. For this, approximately 10% of the total data set was allocated to the test data set. To train the YOLOv7 network on the Jetson Nano computing card, 325 thermal images were used. 295 of these images were used for training and 30 for testing. All of the images used in training consist of defective solar panels.

Test flights were carried out on solar panels with the developed unmanned aerial vehicle. YOLOv7 network was trained with the recorded thermal image data and fault detection application was performed. The experiments conducted within the scope of this study were carried out on solar panels at Izmir Bakırçay University. The solar panels on the car park of Izmir Bakırçay University are as shown in Figure-14.

Figure 14. Izmir Bakircay University Solar Panels [33]

A UAV with a thermal camera module was flown over the solar panels and thermal images of the panels were recorded in the memory (SD card). The images recorded in the memory were uploaded to the Jetson Nano computing card and the errors in the images were detected. The studies were carried out on a sunny day in August. On a day with an average air temperature of 30-40 °C, the time interval between 13:00 and 15:30 was preferred. Some results are shown in Figure-15 and Figure-16 below.

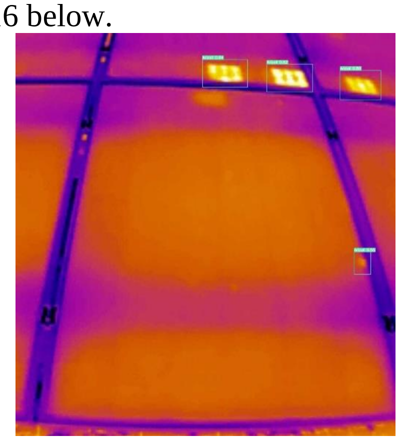

Figure 15. Test Data-1

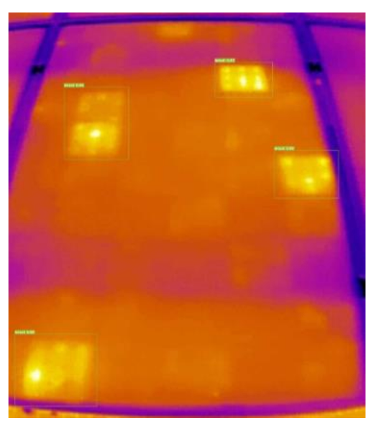

Figure 16. Test Data-2

The details of the data set used in the training are given in Table-1. According to the table, a total of 325 data were used in the training, of which 295 were faulty and 30 were intact.

Tablo 1. Data Set

	Train	Test	Total
Fault	275	20	295
Without Fault	20	10	30

The YOLOv7 network has various performance criteria. These are accuracy, precision, sensitivity and F1 score.

Performance Criteria, Performance Criteria to evaluate the performance of a model Metrics such as Positive True (True Positive, TP), Positive False (False Positive, FP), Negative True (True Negative, TN) and Negative False (False Negative, FN) are used to evaluate the performance of a model. Positive True means that the model correctly identifies an image containing an error as an error, while Positive False means that an image that is actually error-free is classified as an error. Negative True indicates that the image is error-free and the model correctly predicts this. Negative False indicates that although there is an error in the image, the model fails to detect it. The metrics used to measure the success of the model include Accuracy, Precision, Sensitivity and F1 Score. Accuracy gives the success rate of the model in all predictions and is calculated as the sum of true positive and true negative predictions divided by all predictions. The mathematical expression of this calculation is given in Equation 1.

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

Equation 2 refers to the calculation of precision. Precision indicates the success of the model in correctly predicting the positive class and is calculated as follows: True Positive (TP) divided by the sum of the number of True Positive and False Positive (FP). This metric gives the ratio of true positive predictions made by the model to all positive predictions.

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

Equation 3 shows the sensitivity calculation. Sensitivity measures how well the model can detect true positive classes. This metric is the number of True Positive (TP) divided by the sum of the number of True Positive and False Negative (FN). Sensitivity reveals how successful the model is without skipping the positive class.

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

Equation 4 shows the calculation of the F1 score. The F1 score is used to balance the performance of the model in terms of both precision and sensitivity. This score is obtained by taking the harmonic mean of precision and sensitivity. The F1 score is an effective metric for evaluating the overall performance of the model, especially when there is imbalance between classes.

$$\text{F1 Score} = \frac{Precision * Sensitivity}{Precision + Sensitivity} * 2 \qquad (4)$$

The performance values of the study are shown in Table-2 below.

Tablo 2. Results

	Performance Score
Accuracy	0,91
Precision	0.86
Sensitivity	0,90
F1 Score	0,88

The column data in the table represents the class label used in the programme and the row data represents the performance values related to the faults. The detection and diagnosis of the fault was performed with 91% accuracy, 86% precision and 90% sensitivity. The F1 score of the fault class was found to be 88%.

4. Result

In this study, the detection and diagnosis of malfunctions in solar panels has been successfully realized with a deep learning approach using thermal images. The developed UAV system was tested on solar panels placed in the parking lot of Izmir Bakırçay University. The deep learning based Yolov7 algorithm was used to detect and diagnose faults using the images obtained with the thermal camera module installed on the UAV. The images taken with the thermal camera were labeled as Defective and a single class data set was created. The created dataset was trained on Yolov7's model. The training was performed on the computing card Nvidia Jetson Nano device. The training of Yolov7 algorithm was completed with 295 images in 120 steps (epochs). After the training was completed, the test dataset was tested on the model and it was observed that the fault detection gave 91% accuracy. As a result of the tests, it was seen that the success rates obtained from the Yolov7 model were high and sufficient. Considering the way the study was conducted, the use of UAV, thermal camera and deep learning together and the use of the YoloV7 algorithm with UAV for the first time, as far as the research is concerned, speeds up the processes and offers an innovative approach. Retraining the Yolov7 network with thermal images from different types of solar panels will increase the accuracy rate, and using another thermal camera with higher resolution will further increase the success rate.

5. Conclusions

In this study, automatic fault detection was performed using a thermal camera-equipped unmanned aerial vehicle (UAV) and deep learning-based YOLOv7 algorithm for early detection of faults in solar energy systems. The model trained with 325 thermal images yielded successful results with an accuracy rate of 91%. This approach makes a significant contribution to preventing possible costly faults by increasing the effectiveness of maintenance processes in photovoltaic systems.

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