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A Review of Deep Learning-Based Defect Detection and Panel Localization for Photovoltaic Panel Surveillance System

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ABSTRACT

As the photovoltaic (PV) systems expands globally, robust defect detection and precise localization technologies becomes crucial to ensure their operational efficiency. This review introduces an integrated deep learning framework that leverages Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and You Only Look Once (YOLO) algorithms to enhance defect detection in solar panels. By integrating these technologies with Global Positioning System (GPS) and Real-Time Kinematic (RTK) GPS, the framework achieves unprecedented accuracy in defect localization, facilitating efficient maintenance and monitoring of expansive solar farms. Specifically, CNNs are employed for their superior feature detection capabilities in identifying defects such as microcracks and delamination. RNNs enhance the framework by analyzing time-series data from panel sensors, predicting potential failure points before they manifest. YOLO algorithms are utilized for their real-time detection capabilities, allowing for immediate identification and categorization of defects during routine inspections. This review's novel contribution lies in its use of an integrated approach that combines these advanced technologies to not only detect but also accurately localize defects, significantly impacting the maintenance strategies for PV systems. The findings demonstrate an improvement in detection speed and localization accuracy, suggesting a promising direction for future research in solar panel diagnostics. The review provided aims to refine surveillance systems and improve the maintenance protocols for photovoltaic installations, ensuring longevity, durability and efficiency in energy production.

1. Introduction

As solar energy adoption grows, effective monitoring and maintenance of photovoltaic (PV) panels are crucial to ensure their efficiency [1]-[3]. However, traditional manual inspection methods are costly, time-consuming, and prone to errors, highlighting the need for more efficient solutions [4]-[7]. To address these challenges, the project aims to develop an intelligent surveillance system using deep learning algorithms and a drone equipped with thermal imaging and cameras. Thus, this paper will focus on the review of PV surveillance system development which covers deep learning concept, defect detection, and localization of defected solar panels. The system will automate the detection and diagnosis of PV panel issues, offering a more accurate and efficient alternative to manual inspections. The system will utilize a drone to capture thermal images of PV panels. Deep learning algorithms will then analyze these images to identify various defects, including fractures, hotspots, delamination, and dust. A comprehensive dataset of labeled thermal images will be collected for training and testing the algorithms. The system will be able to recognize intricate patterns that point to flaws by utilizing deep learning, enabling precise and instantaneous detection [8]-[12]. The deep learning method for defect identification will be developed and optimized as the main goal of the project. A dataset of labeled thermal pictures for both testing and training will be gathered. Even with a minimal amount of labelled data, the algorithm will be refined and adjusted to enhance its detection skills. The system's performance will be rigorously assessed through experiments in diverse environmental conditions. Key evaluation metrics will include detection accuracy, response time, and robustness across different scenarios. The objective of the project is to overcome the drawbacks of human inspection techniques by automating flaw identification in PV panels. The technology provides an accurate and economical means of maintaining and monitoring PV installations. This promotes the long-term viability and efficiency of solar power systems and opens the door for a larger uptake of renewable energy sources. The primary contributions of this research are firstly the development of an advanced deep learning framework that integrates CNNs, RNNs, and YOLO for comprehensive defect detection in solar panels. This framework significantly enhances detection accuracy by leveraging the strengths of each technology. Secondly, this study develops the application of RTK GPS for precise localization of defects on solar panels, which facilitates targeted maintenance actions and optimizes the operational efficiency of solar farms [13]-[15].

Despite advancements in drone-based infrared thermography for PV panel fault detection, several limitations persist. Existing methods often focus on defect identification but lack precise localization of faulty modules, making timely repairs challenging. Researchers from all over the world have been investigating infrared thermography as a means of more accurate solar panel fault identification. [16] suggested a novel monitoring system that makes use of unmanned aerial vehicles (UAVs) to detect the failure of numerous solar panels. As monitoring tools, cameras with optical and thermal imaging capabilities were used to look at PV power facilities. PV system defects and malfunctions are detected via thermography analysis by a tool developed by [17]. Their strategy allowed them to identify the heated temperature zone in the infrared photographs. The original image was converted to greyscale before Gaussian filtering was applied to reduce noise. The hot and cold PV module zones were then distinguished in the acquired pictures using the binary model. Lastly, the panel's boundary area was determined, and the problematic areas' features were displayed using the Laplacian model. A similar approach was proposed in [18], by the person who estimated the boundary area and degradation.

A drone was utilized in [19] to take pictures at different altitudes in order to investigate the relationship between picture capture height and possible PV module defect detection. These methods in [16]-[19] are limited to identifying defects; they are unable to locate a malfunctioning PV module precisely. This limitation makes it more challenging to promptly repair broken modules once they are identified. The image processing pipeline proposed in [18] includes automatic detection of individual solar modules, infrared thermography analysis of malfunctioning modules, and classification into three basic groups: hot areas, overheated substrings, and overheated modules. In [20], a drone-based system for utilizing thermal and RGB pictures to identify solar panel defects was also suggested. To discover the solar panel array, they used RGB photographs; to find the broken panels, they used thermal images. These techniques [18], [20] can identify and pinpoint the problematic modules, even when their evaluations have been conducted on small datasets or in simulated situations. While some research has addressed fouling detection in commercial PV systems, this project builds on these efforts by integrating advanced deep learning techniques and drone-based thermal imaging to provide a more comprehensive and accurate monitoring solution.

In conclusion, the research contributions of this review are twofold. Firstly, it discussed towards the development of a unified deep learning model that enhances the accuracy and speed of defect

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detection in photovoltaic systems. Secondly, it introduces an innovative use of RTK GPS technology for the precise localization of identified defects, thereby significantly improving maintenance strategies for solar farms.

2. Deep Learning Concept

Deep learning is a subfield of machine learning that utilizes artificial neural networks with multiple interconnected layers to learn and extract meaningful features and representations directly from data, enabling more accurate decision-making and prediction. The deep learning models have the capability to learn complex patterns and relationships within the data, which traditional machine learning techniques often struggle with. Consequently, deep learning approaches, such as Convolutional Neural Networks, are able to make more accurate predictions compared to conventional methods, especially for complex image data like solar panel surfaces [21], [22]. Unlike traditional image processing techniques that rely on manually engineered features and thresholds, deep learning models automatically learn the optimal features for defect recognition directly from the data, resulting in more robust and accurate detection under variable lighting and weather conditions. This allows for enhanced performance in critical applications like solar panel inspection and maintenance, where reliable fault identification is essential for maintaining system efficiency. Deep neural network's overall structure is multilayers of nodes connected to each other, therefore making the set possible to learn increasingly complex representations of input data. This general learning approach has lately proven quite successful with applications including image recognition, speech recognition, and natural language processing, where it delivers superhuman performance in certain cases. The large number of model parameters in deep neural networks requires specialized hardware, such as graphics processing units (GPUs), to train and run the models efficiently [23], [24].

One of the most important aspects of deep learning is to achieve the right balance between model complexity and performance. Too complex models can lead to results that are overfitted to the training data but fail on new data, whereas overly simple models might not capture all relevant patterns in the data. Implementing intelligent systems that are machine learning- and deep learning-based has challenges in terms of issues such as explainability, fairness, and robustness, all leading to full trustworthiness and dependability of the devised systems [25]. More general, for researchers and practitioners in the field of computer science, data science, and artificial intelligence, it is necessary to develop an overall understanding of deep learning through the concepts and processes involved. Business or economics researchers and practitioners who plan on applying these techniques to problems of interest in practice might also benefit from it. As shown in Fig. 1, the overview of Artificial Intelligence, Machine Learning, and Deep Learning, while Fig. 2 shows the difference between deep learning and traditional machine learning.

2.1. Convolution Neural Network (CNN)

The Convolutional Neural Networks belong to a class of artificial neural networks designed to work with image and video recognition tasks. CNN is made up of several layers, namely: the convolutional layer, the pooling layer, and the fully connected layer. The convolutional layers identify characteristics in an input image, such as edges, corners, and other patterns. They do this by applying a fixed set of filters on the input image that convolves with the image and produces a set of feature maps. In turn, these feature maps flow through a non-linear activation function such as ReLU, which introduces non-linearity in the network [27]-[29]. In defect detection, convolutional layers are crucial as they act like a set of learned filters. For instance, one layer might detect edges of cracks in a solar panel, while another could identify changes in texture due to delamination. By stacking multiple layers, the network can detect complex defect patterns at different scales and depths, crucial for accurately identifying varied defects across diverse solar panel conditions. Pooling layers generally take the output of convolutional layers as input and reduce the dimensionality of the feature maps that convolutional layers produce, therefore also reducing the quantity of space the input data will occupy. This makes the network computationally efficient. The typical operations associated with pooling are max pooling and average pooling. Pooling layers reduce the dimensionality of the data processed by the convolutional layers, which helps in reducing computational costs and overfitting. For solar panels, pooling might summarize the presence of small-scale defects across larger areas of the panel, ensuring that such defects are still recognized even after substantial downscaling of the image resolution. Fully connected layers classify the input image based on the features detected by the convolutional layers. They take the input from the flattened output of previous layers and produce a set of class scores by applying a set of weights to it, which is then passed through a softmax function to get the probability distribution over the classes [26]. At the end of the CNN architecture, fully connected layers compile the features extracted by convolutional and pooling layers to make final predictions. They might classify a segment of a solar panel image as 'defective' or 'non-defective' based on the presence of characteristic defect features such as cracks or hotspots. One of the key advantages of CNNs is their ability to learn hierarchical representations of the input data. As this input propagates through the layer of the network, it becomes increasingly abstract, with low-level features such as edges and corners becoming combined into higher-level features such as forms and objects [28]. Convolutional Neural Networks (CNNs) were specifically adapted to extract and analyze textural and morphological features from high-resolution images of the panels. These networks are designed with layers fine-tuned to enhance sensitivity to cracks and degradation patterns that are typical in worn or damaged PV cells. Fig. 3 shows learned features from a CNN.

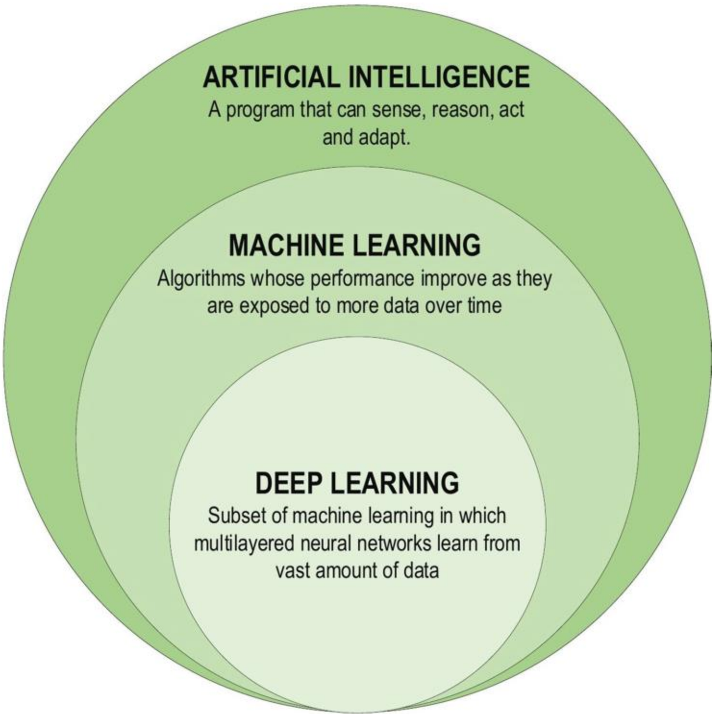

Fig. 1. Deep learning family [26]

2.2. Recurrent Neural Network (RNN)

There exists a special kind of Artificial Neural Network for dealing with the task of processing the sequence of input data, called Recurrent Neural Networks, or RNNs for short. What primarily distinguishes them from normal, traditional feedforward artificial neural networks is the presence of an internal memory. An RNN can be used to store information about some input, for example, previous timesteps in a sequence, using an intermediate representation known as a hidden state. The reading of new words makes this memory, which is in a hidden state, change from the previous state. A sequence of data points is naturally fitting for RNNs. Applications for this include speech recognition, time series analysis, video processing, natural language processing, and so on. However, the vanishing gradient problem poses the most severe barrier to their ability to capture long-range connections among data points. In reaction, there were further developed RNN variations. Thus, long short-term memory and gated recurrent units are nowadays much more complicated, which allows them to have specific gating mechanisms to perform in combination with sequential input [30], [31]. Therefore, RNNs remain the basic units of deep learning for tasks that deal with sequences of data. They are based on robust, powerful time pattern modeling and representational capabilities [26]. While primarily the project uses CNNs for static image analysis, RNNs hold potential for future enhancements. If time-series data of solar panel conditions are captured, RNNs could be instrumental in tracking the progression of defects over time. This could be critical for predictive maintenance, where understanding how defects evolve could preemptively inform repair schedules and prevent major failures [21]. CNNs were selected for their superior capability in spatial feature extraction, which is pivotal when analyzing images for physical defects. Recurrent Neural Networks (RNNs) are employed to process sequential data from the panels' output over time, providing predictions on potential failure points based on historical degradation trajectories [22]. While other models such as Support Vector Machines (SVM) and Decision Trees were considered, CNNs and RNNs were found to be more effective based on previous researchers, demonstrating higher accuracy and reliability in handling the complex dataset composed of diverse imaging conditions [32].

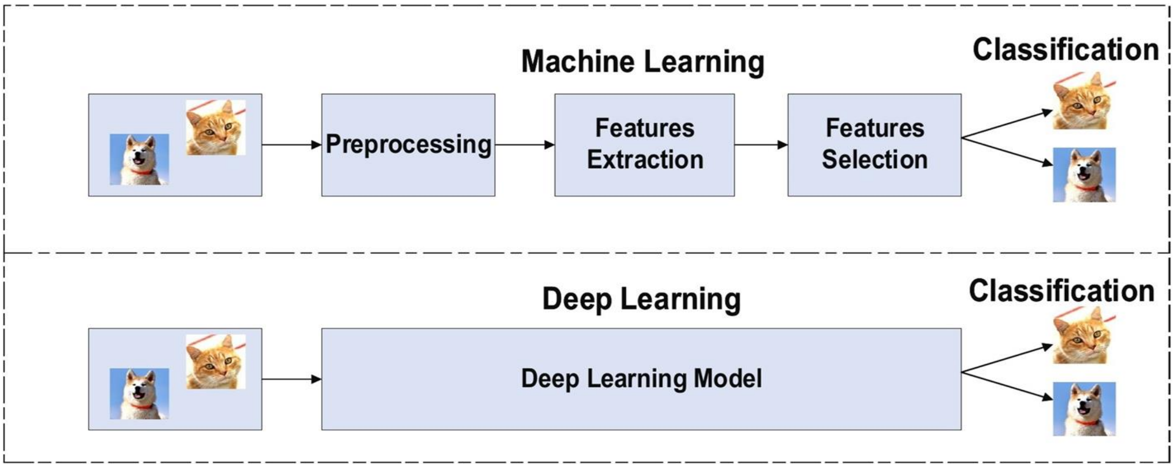

Fig. 2. The difference between deep learning and traditional machine learning [26]

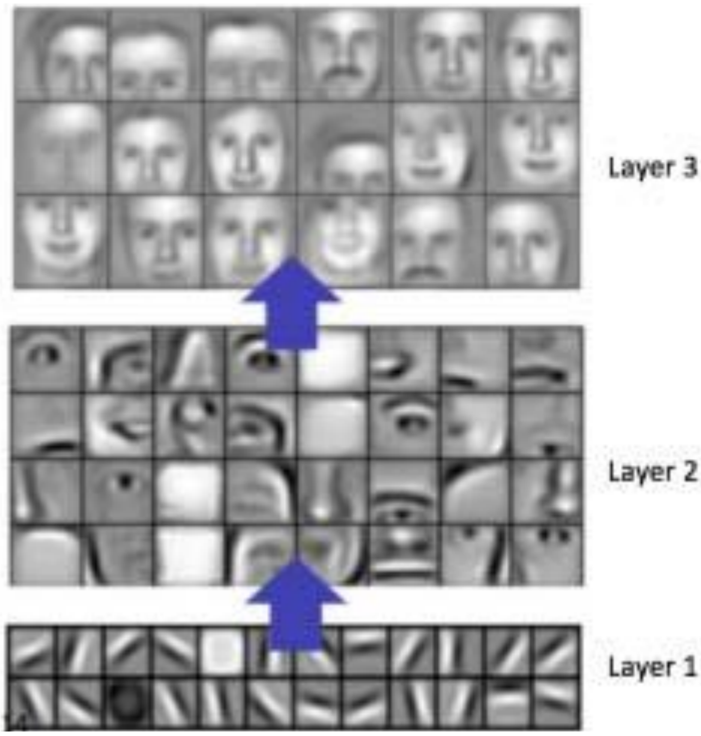

Fig. 3. Learned features from a convolutional neural network [28]

2.3. You Only Look Once (YOLO)

One of the well-known object detection algorithms is the YOLO (You Only Look Once) algorithm. It was first introduced in 2015 and provides speed and efficiency by using a single neural network to predict bounding boxes and class probabilities directly from full images in one evaluation [33], [34]. This differs from other object detection algorithms, including Faster R-CNN and Single Shot Detector (SSD), which rely on multi-stage processes to achieve object detection. YOLO has been popular ever since its arrival and, correspondingly, fine-tuned over versions v2, v3, v4, and v5 with improved accuracy, speed, and features. For example, YOLOv2 introduced the anchor box to predict the bounding box more precisely, and YOLOv3 made use of the feature pyramid network to detect objects on different scales. YOLOv4 has introduced the bag of freebies and the bag of specials that enhance algorithm accuracy and speed. YOLOv5 introduced a new architecture: using only one anchor box for each grid cell and a new loss function which enables superior accuracy of small objects [35].

In January 2023, Ultralytics, the company that released YOLOv5, made an official announcement for the release of YOLOv8, the newest member of the YOLO family. First comparisons of the new kid over its predecessors start showing its superiority as the new YOLO state-of-the-art, even though a paper release is soon and many features are still missing from the YOLOv8 repository [34]. From Fig. 4, it can be seen that all the YOLO-v8 variants have better throughput relative to the other YOLO versions trained with 640 image resolution [36]. These are realized with a similar number of parameters and, hence, highlight hardware-efficient architectural reforms even further [37], [38]. Since both YOLOv8 and YOLOv5 were introduced by Ultralytics, presenting amazing real-time performance, and given the initial benchmarking results that Ultralytics published online, most likely YOLOv8 will be oriented to constrained edge-device deployment with high inference speed. In the review, a systematic outline of the methodological frameworks employed in the studies analyzed is presented, focusing on the application of deep learning techniques CNNs, RNNs, and YOLO algorithms in defect detection for photovoltaic systems. The analysis includes a critical examination of the selection and use of model hyperparameters, training procedures, data preprocessing techniques, and validation methods [39], [40]. Analysis using accuracy, precision, recall, and F1-score is necessary for a thorough evaluation. This approach allows for an assessment of the robustness, reproducibility, and effectiveness of each method in the context of current challenges and advancements in the field [41]. The goal is to provide a comprehensive understanding of how these deep learning techniques have been implemented and validated in existing research, thereby identifying gaps and suggesting areas for future exploration. A comparison of YOLOv8 with its previous versions is shown in Fig. 4.

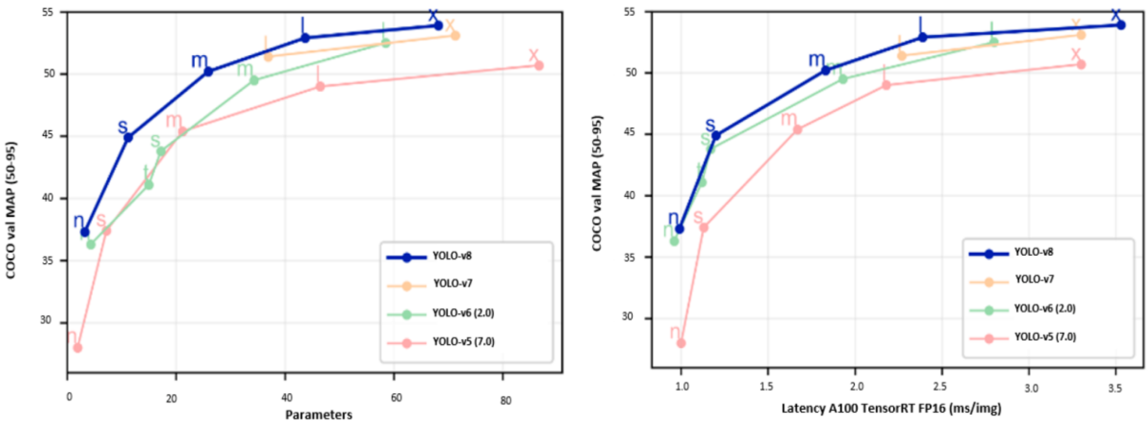

Fig. 4. YOLO-V8 comparison with previous version [36]

Unlike traditional CNNs that may analyze parts of an image in isolation, YOLO looks at the entire image during its detection phase. This holistic approach allows YOLO to detect defects like

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cracks or hotspots more accurately and rapidly, which is vital for inspecting large solar farms. For example, while CNNs might miss a small crack at the corner of a panel due to limited regional focus, YOLO's comprehensive image analysis ensures no part of the image is overlooked, making it ideal for aerial inspections where each pass of the drone must count. Furthermore, the use of YOLO algorithms for real-time detection and localization allows for immediate response to emergent issues, minimizing downtime and improving overall system availability [34].

3. Defected Solar Panel

Deep CNN has emerged as particularly well-suited tools for recognizing various kinds of surface defects in solar panels. A CNN is a class of deep, feed-forward artificial neural networks that are very well suited to the task of image classification. It implements learning by the use of filters where the filters learned from training can extract features from input images to further classify them into different classes. Several research studies have utilized the implementation of CNN to identify defects in solar panels such as cracks, hotspots, and soiling among others [18], [20]. From these studies, it is established that the CNN approach can achieve high accuracies in the detection of defects and trained on large datasets for improved performance. Transfer learning employs the use of a pre-trained neural network in handling new tasks. This is helpful where the data available for training and validation is less and, respectively, enables a network to exploit the acquired knowledge from a larger dataset. In the detection of solar panel defects, transfer learning with AlexNet CNN was put in place to enhance the performance of the network. AlexNet is one of the most popular CNN architectures that was trained on a very large dataset of images and proved to be effective across a very wide range of image classification tasks. Using transfer learning, other studies have already reported enhanced performance of the network in defect detection in solar panels with AlexNet CNN [42].

AlexNet is well-suited for solar panel defect detection due to its robust deep learning architecture, which excels in recognizing complex visual patterns essential for identifying defects such as cracks and degradation on solar panels. Its convolutional layers effectively extract detailed features from images, a crucial capability for analyzing the subtle and varied defects that can occur across different types of solar panels and under various lighting conditions. The adaptability of AlexNet allows it to adjust to new data, making it highly effective for ongoing monitoring and maintenance of solar panel efficiency, ensuring they operate optimally under diverse environmental conditions [42], [43].

3.1. Type of Defects

Solar panels can have a wide range of flaws that could impact not just efficiency but also overall performance. These flaws can include dust accumulation on the panel surface, electrical malfunctions like hotspots, and structural flaws like cracks and delamination [44], [45].

3.1.1. Cracks

Physical destruction on the surface of the solar panel could be cracking, breakage, damage to the top cover glass, or even harm to the solar cells by themselves. Most of the above-mentioned defects could come as a result of severe weather, debris impact, manufacturing defects, thermal stress, mechanical stress during installation, and transportation. Besides reducing the efficiency and possibly causing electrical problems, a crack may bring a decrease in electricity output as well as cause a risk to the structure of the panel [46], [47]. Cracks can be originated by different causes, such as variation of temperature, mechanical stressors, manufacturing defects, and even installation problems. CNN utilizes specialized edge-detection filters within its convolutional layers to identify linear and jagged patterns typical of cracks. Training images labeled with these defects help the network to learn and recognize subtle variations in crack appearances across different panel types and conditions [48], [49]. Examples of the cracks on the solar panels are presented in Fig. 5.

3.1.2. Hotspots

Hotspots are areas of exceptionally high temperature in any photovoltaic module; they are a warning indication of potential issues with nearby solar cells or components. A common cause is a mismatch in the current flow of different solar cells, which results in localized heating. Hotspots are caused by partial shading, even in very small areas of the panel, as it increases resistance and blocks current flow [51], [52]. For hotspots, CNN is trained on thermal images where hotspots manifest as regions with higher temperature signatures. The network learns to associate specific color and intensity patterns within these thermal images with potential hotspots, enabling it to quickly flag areas needing further inspection [53]. Solar panel hotspots are shown in Fig. 6.

Fig. 5. Cracks on solar panel [50]

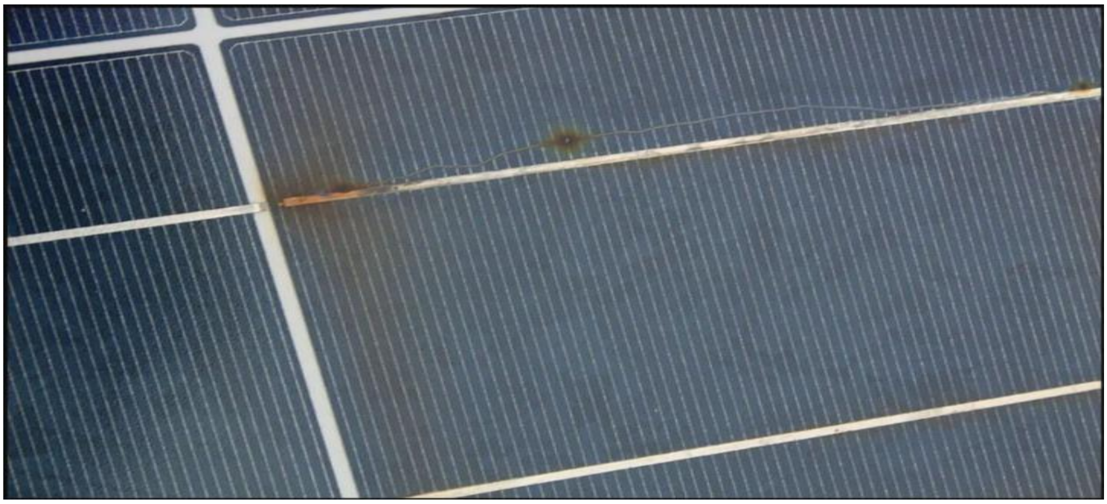

Fig. 6. Hotspots on solar panel [50]

3.1.3. Delamination

Delamination is the process of separation between some layers in the solar panel, such as the backsheet and encapsulating material layers. Its few causes are moisture intrusion, temperature stress, and suboptimal manufacturing procedures. This could let moisture in, which could potentially lead to hotspot formation, corrosion, decreased electrical performance, and many other issues that could further harm the panel [45], [51]. CNN is trained to recognize these irregular patterns by focusing on the textural differences that delamination presents in thermal images. By employing layers that can detect subtle disruptions in expected thermal uniformity, the model learns to flag these as potential delamination sites [22]. Fig. 7 shows delamination on solar panels.

3.1.4. Dust

On the surface of the solar panels, an accumulation of dirt, dust, pollen, bird droppings, air pollution, or other debris can restrict the quantity of sunlight reaching the cells, affecting their efficiency, and resulting in a reduction in power output. To reduce the negative consequences of soiling, routine maintenance and cleaning are required [42], [45]. CNN uses pooling layers to effectively downscale the image while retaining the characteristic features of broad, uniform coverage that indicates dust. This allows the model to differentiate between widespread thermal changes caused by dust and more localized anomalies indicative of other types of defects. Fig. 8 shows dust on solar panels [22].

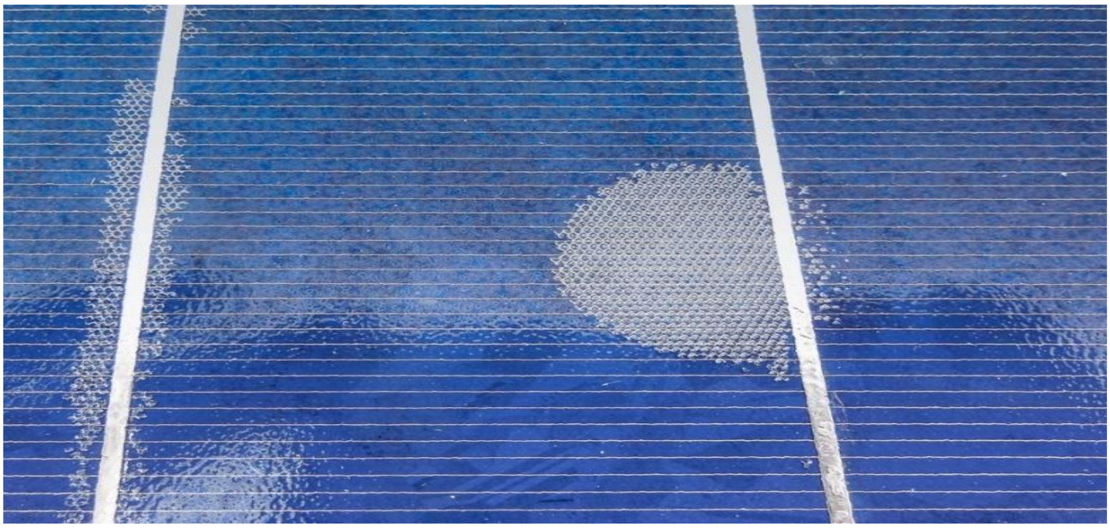

Fig. 7. Delamination on solar panel [50]

Fig. 8. Dust on solar panel [50]

3.2. Thermal Image

Thermal imaging where it used infrared sensor. It is a technique that shows and tracks the temperature distribution of surfaces and objects. This technique is widely used to find flaws in solar panels in a variety of fields, including industry, building inspections, medical diagnosis, and this project. All objects emit infrared radiation, or heat, which is a form of electromagnetic waves. The wavelength and intensity of this radiation are influenced by the object's temperature. Despite being undetectable to the human eye, thermal imaging cameras and sensors can detect this radiation [42]. Thermal imaging cameras can detect and capture these infrared emissions, converting them into visual representations that show variations in color or shade representing temperature changes over a surface. Warmer parts manifest as brighter colors, while cooler zones display darker colors [54]-[56]. Thermal images undergo several preprocessing steps to enhance defect visibility for the CNN. This includes contrast enhancement to make temperature differentials more distinct and noise reduction to eliminate background thermal fluctuations that might obscure true defects. The CNN then analyzes these preprocessed images, using layers trained to identify thermal patterns associated with typical defects like hotspots or shadow effects caused by debris accumulation.

While thermal imaging is praised for its ability to detect anomalies like hotspots which are indicative of potential failures, its effectiveness can be significantly influenced by environmental factors. For instance, thermal cameras are less effective in cooler ambient temperatures where the contrast between defective and non-defective areas is reduced. Additionally, the angle at which solar panels are installed can affect the thermal gradient visible to sensors [57]. A study by [58] highlighted that thermal imaging could misinterpret shadow-induced temperature variations as defects, leading to false positives. These environmental sensitivities necessitate calibration adjustments and possibly the integration of complementary sensors to enhance diagnostic accuracy under variable conditions. Fig. 9 and Fig. 10 show the indoor thermography setup and outdoor thermography setup respectively.

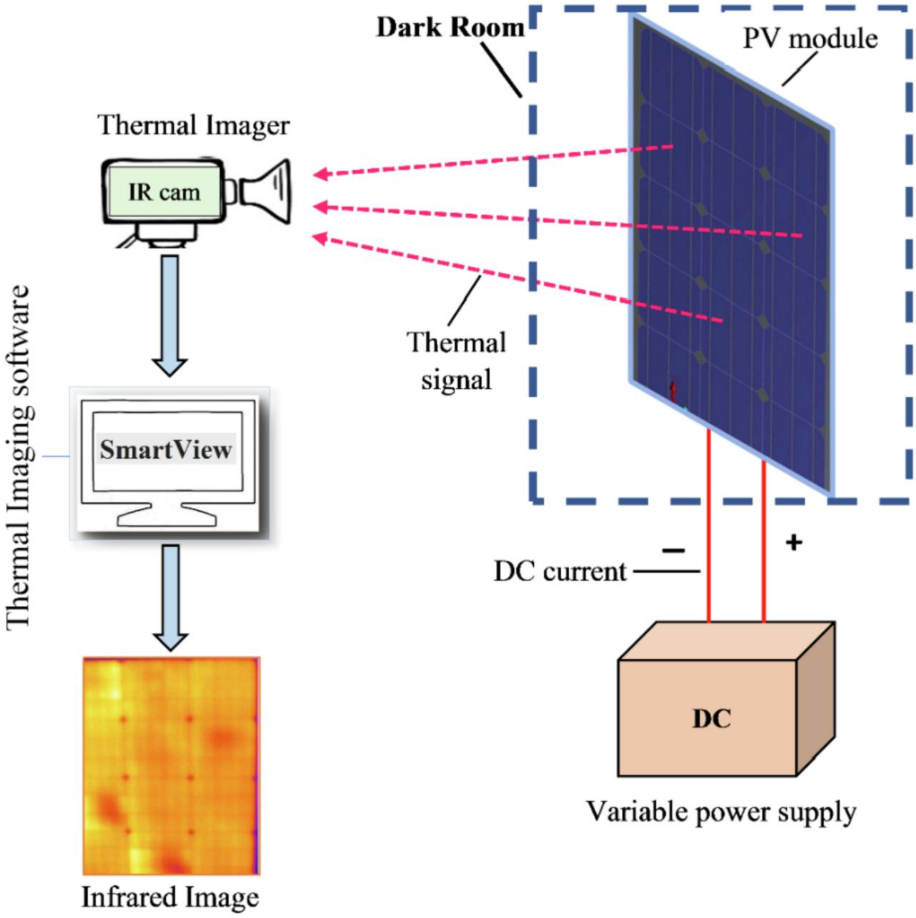

Fig. 9. Indoor thermography setup [59]

3.3. Detection Technique for Solar Panel Defects

By using deep learning methods, it is possible to automatically spot abnormalities or defects in images of solar panels by the training model in an order of steps that is data collection, pre-processing, convolutional neural network (CNN), transfer learning, anomaly detection, classification and deployment. Fig. 11 shows the flowchart of solar panel defect detection process.

The proposed flowchart begins with Data Collection, where drones equipped with thermal cameras capture images of the solar panels. The next step, Image Preprocessing, involves adjusting image quality and isolating key features. Following this, Model Training occurs, where CNN learns from labeled defect images. Defect Detection is the operational phase, where the trained model analyzes new images to identify defects. The final step, Feedback Implementation, involves reporting detected defects for maintenance scheduling. This flowchart not only illustrates the process but also underscores how each phase is interconnected to optimize defect detection.

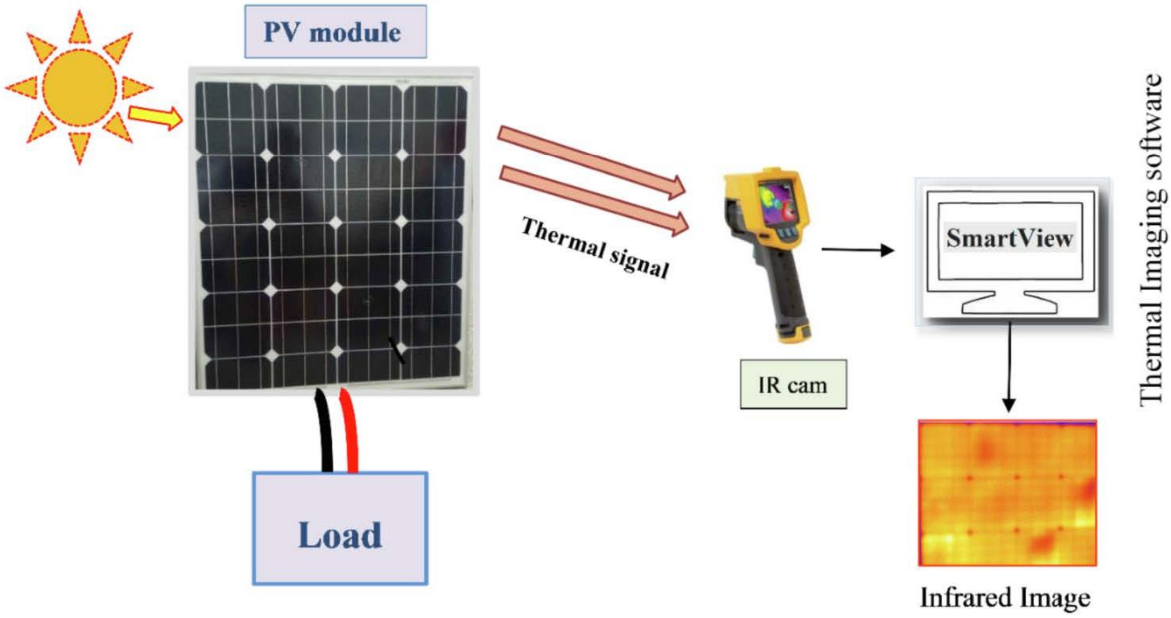

Fig. 10. Outdoor thermography setup [59]

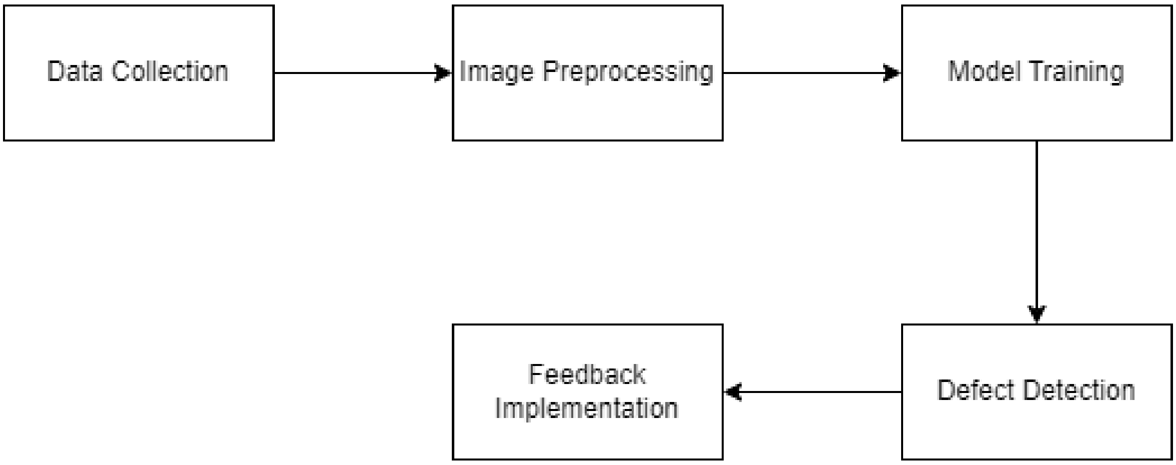

Fig. 11. Flowchart of solar panel defect detection process

3.3.1. Data Collection

In this stage, it is important that photos be collected on a large scale showing both typical solar panels and those with various defects. Various types of defects, lighting conditions, and angles must be present in this data set. An outstanding sample is required to train a competent deep learning model [60]-[62]. However, it is also crucial to consider the quality of images and the representation of various environmental conditions within these datasets.

3.3.2. Pre-Processing

The input data must be pre-processed before it is fed into the neural network. This may involve resizing images to the same size, normalizing pixel values, and rotating, cropping, or flipping images to potentially include more images in the dataset. The model becomes more reliable and generic with increasing data addition [63]. The pre-processing stage is expanded to detail the technical challenges and necessary trade-offs. Resizing images, for instance, can impact the model's ability to detect smaller defects such as micro-cracks. While resizing helps in standardizing input dimensions for neural networks, it may inadvertently smooth out or erase critical defect details. To mitigate this, techniques such as using higher resolution settings or adaptive resizing methods that preserve edge details are considered. Furthermore, the computational cost and complexity of pre-processing operations, including normalization and augmentation, are discussed. These processes, while crucial for model training by providing varied, yet consistent data, require substantial computational resources, potentially increasing the time and expense involved in model training.

3.3.3. Convolution Neural Network (CNN)

An exceptionally fine design under deep learning for works related to images is the Convolutional Neural Network. It is made up of layers that identify hierarchical features independently from the input images. In general, convolutional layers are used to extract features, pooling layers are applied for down sampling, and fully connected layers perform classification. Basically, a CNN is going to gather patterns and characteristics by which the detection of flaws can be enabled [64], [65].

3.3.4. Transfer Learning

Transfer learning fine-tunes a pre-trained CNN model toward the specific task of defect detection in solar panels. General features are provided to the pre-trained model through the large datasets, which means the pre-trained model can improve the performance for that task. The last layers of the pre-trained model can be replaced, matching the number of classes that are present in the dataset, that is the categories for the defects [44].

3.3.5. Anomaly Detection

Training a deep learning model to differentiate between functioning and malfunctioning solar panels is a step in the anomaly detection process. Anomaly refers specifically to any deviation from the norm that indicates a potential defect impacting the solar panel's performance. This includes both observable defects like cracks and hotspots, as well as subtler deviations that may not immediately impact panel efficiency but could lead to future failures. The patterns linked to these anomalies ought to be detectable by the model [21].

3.3.6. Classification

After being trained, the deep learning model can differentiate between images that are normal and those that have a specific defect. At this stage, the model will assess the features it has extracted from the input image and designate a label that indicates whether the panel contains defects or not. Several output classes could be included in the model, based on the quantity and type of defects that should be found [63]. Anomaly refers specifically to any deviation from the norm that indicates a potential defect impacting the solar panel's performance. This includes both observable defects like cracks and hotspots, as well as subtler deviations that may not immediately impact panel efficiency but could lead to future failures.

3.3.7. Distribution

The model can be used to perform inference on new images of solar panels in batch or real-time once it has been trained and verified. This can be done in a few different ways, such as by integrating the model into an automated inspection system, a mobile application, or a web application. Ensuring the model's predictions are accurate and dependable in practical situations is crucial during the deployment phase [66], [67].

4. Localization of Solar Panel

Real-Time Kinematic GPS is an advanced satellite navigation technology that provides highly accurate real-time positioning capabilities. This system operates on the principle of triangulation, utilizing a mobile rover receiver and a stationary base station with known precise coordinates. The base station continuously tracks signals from GPS satellites and calculates real-time corrections for various error sources, such as atmospheric conditions. These corrections are then transmitted to the rover, enabling it to fine-tune its position calculations to the centimeter level. The distinction between an RTK solution that is "fixed" versus "float" lies in the stability of the connection between the rover and the base station. A fixed solution, with a stable connection, can consistently achieve centimeter-level accuracy. Conversely, a float solution may experience occasional connection disruptions, leading to slightly diminished accuracy in the range of a few centimeters [68]-[70]. Despite its exceptional precision, RTK-GPS technology faces some challenges. Signal interference from physical and atmospheric conditions can disrupt the accuracy of location data. Furthermore, the technology requires a clear line of sight between the GPS antenna and a minimum number of satellites, which can be obstructed in dense urban or forested areas. To mitigate these issues, users can employ signal augmentation systems and strategically choose installation sites with minimal obstructions [71].

Applications for RTK GPS include cases where accurate land surveying is necessary, construction site mapping, self-driving vehicles, and drone navigation. In implementing RTK GPS systems, factors need to be taken into account on issues such as potential obstruction, signal interference, and equipment costs, regardless that it provides accuracy on levels never seen before. All in all, RTK GPS is an important technology for sectors and applications that need extreme levels of real-time spatial positioning precision [72], [73]. The Radio Technical Commission for Maritime Services (RTCM) is responsible for establishing maritime communication and navigation technology international standards. Though RTCM majorly focuses on maritime services, its impact extends to technologies like Real-Time Kinematic GPS, which is important for precise positioning for maritime applications. RTCM develops standards for Global Navigation Satellite System (GNSS) augmentation systems, which underpin the interoperability and compatibility of different systems used as part of RTK GPS.

In this way, a harmonized framework is provided in which RTK GPS receivers and base stations of different types implement some common protocols. Take the example of maritime navigation, where RTK GPS will bring about accuracy down to the centimeter level; in such a case, RTCM standards will help in the seamless integration of this technology with other maritime systems. The diversity of the stakeholders from government agencies to private companies guarantees that the standards are comprehensive and address the varied needs of the maritime sector within RTCM. RTCM indirectly influences the implementation of RTK GPS by putting in place a standardized environment for maritime applications that ensures safer and more efficient navigation across the seas [72]. Fig. 12 shows the RTCM Propagation System Design, highlighting how RTCM messages are transmitted from RTK base stations to unmanned aerial vehicles (UAVs). It outlines the role of Networked Transport of RTCM via Internet Protocol (NTRIP) servers and casters in distributing these messages and illustrates their integration with ground control stations for precise UAV navigation.

4.1. Application Using GPS and RTK GPS for Precision Agriculture

Precision agriculture is an integrated technological system that enables optimal farm practices, saving resources and in turn increasing crop yields. In this effort, GPS and RTK GPS are playing major roles. The tractors and other farm machinery guided by GPS can be steered across fields to precision. An RTK GPS system provides sub-inch accuracy controls for different applications like planting, spraying, and harvesting. This minimizes overlap, consequently reducing resource wastage and increasing overall efficiency [74].

RTK GPS allows variable rate application of inputs such as fertilizers, pesticides, and water. By learning about the variability that exists in the conditions of the soil across the field, a farmer can customize the application of resources to be applied at optimal rates in different zones. Such site-specific management contributes to cost saving and environmental sustainability. Similarly, crop health and growth can also be monitored through GPS technology. Drones equipped with GPS fly over the fields taking high-resolution images. The GPS location data accurately indicates the location under analysis. This information is helpful in pictures to make the sites of concern determination, for example, pest infections or nutrient deficiencies. Yield maps, on the other hand, can be adequately prepared by harvesters fitted with GPS and yield monitoring systems. RTK GPS logs the location where different crop yields were harvested [75]-[77]. Farmers can apply this information in future planning and determining in what field places may need certain sorts of attention or correction. Researchers have documented a notable application of RTK GPS in a large-scale solar farm installation in California. The technology enabled the precise alignment of thousands of solar panels across uneven terrain. By leveraging RTK GPS, the project team was able to reduce manual surveying time by 40% and increase the overall energy output by optimizing the orientation of each panel towards the sun [15]. The integration of RTK GPS with computer vision techniques, such as edge detection, holds great promise for enhancing the accuracy, efficiency, and performance of solar power infrastructure deployment and maintenance. These advancements can go a long way in supporting the widespread adoption and optimization of solar energy systems [78]. Fig. 13 shows an agricultural tractor equipped with RTK-GPS technology, demonstrating its application in precision farming. The image highlights the RTK-GPS unit installed on the tractor, which enables precise navigation and field mapping capabilities. This setup allows for highly accurate planting and fertilization, minimizing overlap and reducing resource wastage.

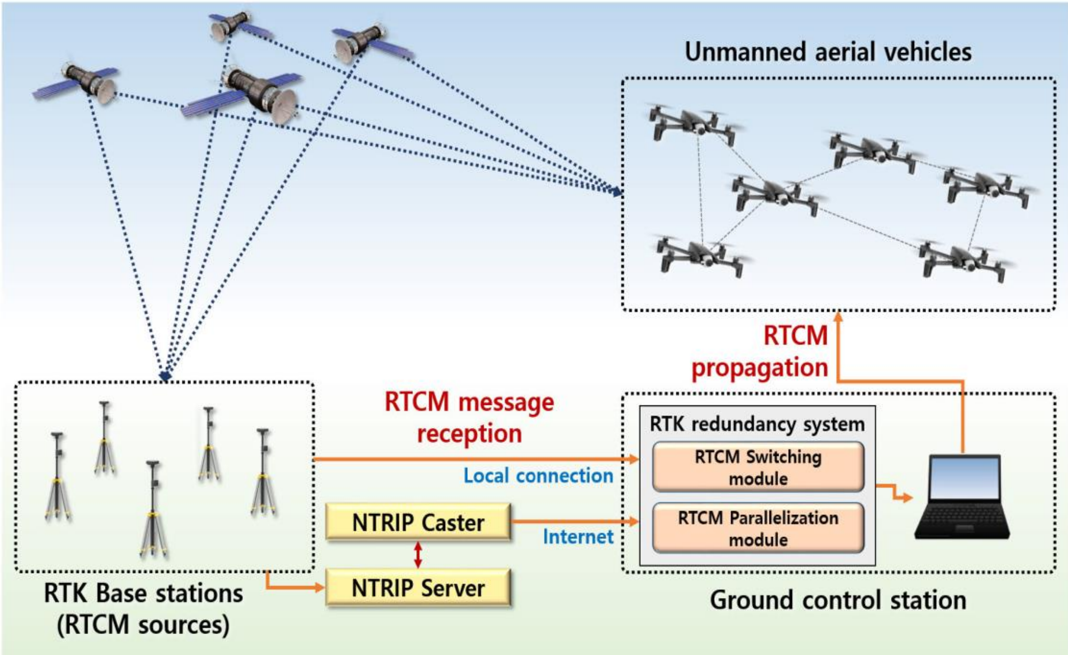

Fig. 12. RTCM propagation system design [72]

To sum up, GPS and RTK GPS technology have had a revolutionary effect on farming, as evidenced by precision agriculture. Resource utilization, waste reduction, and efficiency in general have all undergone significant changes as a result of the precise guidance provided by GPS-equipped equipment and the centimeter-level accuracy offered by RTK GPS. This targeted and data-driven approach, permitted by knowing the variability in the field, does not only contribute to cost savings but also promotes environmental sustainability. Drawing a parallel with respect to renewable energy, the use of RTK GPS for accurate localization of solar panels is also an emerging opportunity area. For instance, the position of solar panels could be optimized very much in the same way as optimizing crop yield, so that they get sun exposure properly and are maintained well. As experience and lessons learned from precision agriculture show, including the benefits of targeted resource application and data-driven decision-making, so too will be the case for efficient management of solar energy resources. This not only supports resilience and sustainability within the agricultural landscapes but also opens an opportunity for more efficient and data-informed solar energy system, versatile capabilities of RTK GPS.

4.2. Method Used in GPS and RTK GPS

Accurate positioning accuracy is very important for the large number of applications in the area of Global Positioning System (GPS) and Real-Time Kinematic GPS (RTK GPS). This calls for some sophisticated techniques and one of them can be regarded as edge detection, along with Machine-Vision Based Edge-Of-Row Detection [80]. Using well-established techniques, such as Canny edge detection, we carry out a step-by-step process to determine important features from an image, in order to enhance accuracy in the data location. This is further made precise by the use of Hough line detection in this process and filtering strategies to screen off unwanted lines [81]. The accuracy of the detected features is guaranteed through a very careful method that includes median filtering of detected lines. Incorporating edge detection algorithms like Canny and Hough transform can significantly enhance the performance of RTK GPS systems. These techniques improve the detection of boundary lines in agricultural fields or solar farms, enabling more accurate delineation of solar panel edges. This is crucial for precise panel placement and alignment, which is essential for maximizing the efficiency of energy absorption. This wider Machine-Vision-based approach fine-tunes accuracy in GPS and RTK GPS location data but also opens up application prospects demanding meticulous spatial awareness. This synthesis of the latest methods contributes to the further development of methodologies used in location determination in view of GPS technologies [82], [83].

Fig. 13. Experiment vehicle with the RTK-GPS [79]

4.2.1. Edge Detection

Edge detection is the most common image processing technique used to detect important changes in intensity within an image, most of which correspond to object boundaries or areas of interest. According to the basic concept, the gradient of the image is computed, representing the rate of intensity change. There are so many famous algorithms for edge detection, and each one has its approach. For example, the Sobel operator uses convolution masks that may measure gradients in horizontal and vertical directions, thus emphasizing edges. The multi-staged algorithm known as the Canny edge detector consists of smoothing the image with a Gaussian filter, calculations of gradients, and the most important steps by applying non-maximum suppression to thin edges, followed by hysteresis thresholding to identify strong and weak edges.

The Prewitt operator is similar to the Sobel and evaluates gradients by convolution masks, and the Laplacian of Gaussian (LoG) consists of smoothing the image and applying the Laplacian operator, which calculates sharp intensity variations [84]. Following the calculation of the gradient, an important process that takes place is thresholding, where identification is made for those pixels, whose gradient values are bigger than some pre-determined threshold into an edge. Hysteresis thresholding in the Canny edge detector is achieved by adding two thresholds for the categorization of edges as strong and weak. While these algorithms remain efficient, they can still be sensitive to noise within an image. Here, some preprocessing methods using Gaussian smoothness are normally introduced for noise reduction prior to edge detection.

The sizes of filters and threshold values are to be tuned properly for enhancing performance. Moreover, certain orientations are sensitive to the specific edge detection algorithms. Edge detection finds enormous usage in practical applications that are domain based. For example, in computer vision, it is at the base of object recognition and image segmentation; in medical imaging, edge detection helps to identify structures or boundaries, which makes jobs like tumor detection much easier. For detection of defects in certain defect detection scenarios, edge detection can be effectively used to make clearer any cracks or other irregularities so that defects may be properly identified and analyzed. Generally, edge detection is the fundamental tool that provides most of the information regarding the structure and features in the image, yielding plenty of image-processing applications [85].

4.2.2. Machine-Vision Based Edge-Of-Row Detection

The furrow location of the autonomous vehicle is determined by these two edges with the use of machine-vision-based edge-of-row detection algorithms. The detection result is the pixel coordinates for two straight lines of the two furrow edges. Fig. 14 shows the flowchart of the machine-vision-based edge-of-row detection algorithm. It illustrates the step-by-step process employed by the machine-vision system to detect edges of rows within agricultural fields or other applications. This flowchart outlines the algorithmic steps involved, from image acquisition to the final edge detection output, emphasizing the role of machine vision in navigating and mapping precise lines.

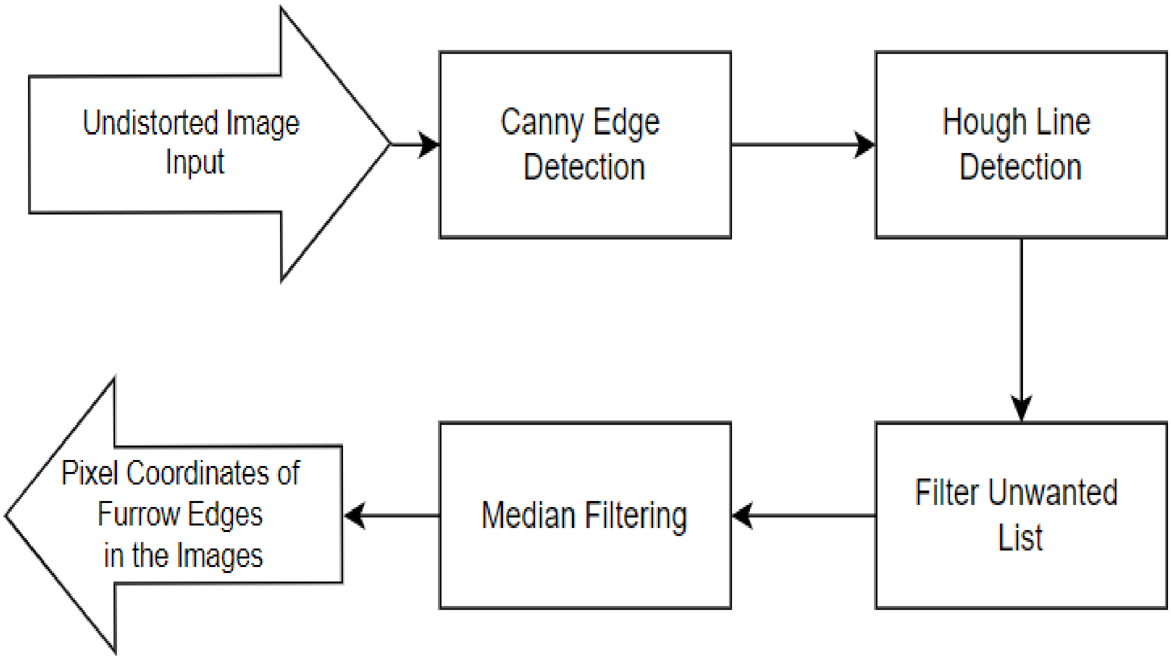

Fig. 14. Flowchart of the machine-vision based edge-of-row detection algorithm

Canny edge detection is one of the most widely used algorithms in image processing as it can find edges in an image very accurately, and its error rate is very low. The method used for detecting edges has been in wide use since 1986 when it was founded by [86]. First is the process of smoothing the image using the Gaussian filter to remove noise and prevent false edge detection. Then convolution with Sobel operators is done to get the gradient magnitude and orientation of the image. After that, non-maximum suppression thins the detected edges by preserving only local maxima in the gradient magnitude. Further increasing edge continuity, Canny edge detection also performs hysteresis thresholding. It categorizes the edges into either "strong" or "weak" based on gradient magnitude thresholds, whereby strong edges are preserved and weak ones retained only if connected to strong edges. The output will be a binary edge map in which the edges are properly defined, and the underlying structure of the image is accurately represented. Canny edge detection is applicable for very precise edge localization, such as in computer vision, object recognition, and image

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segmentation. The multistep approach of the algorithm makes it robust in dealing with many characteristics of images and noise levels [84], [85]. Fig. 15 (a) displays the initial image used as input for edge detection algorithms in the context of precision agriculture or other applications requiring line detection. It shows the raw data that the algorithms analyze, and Fig. 15 (b) shows the output after applying the Canny edge detection algorithm to the input image. It highlights the detected edges, showcasing the algorithm's effectiveness in identifying boundaries and lines crucial for navigational purposes. These images illustrate how the Canny edge detection method can be applied to real-world images, allowing us to extract valuable navigational data. By comparing the original and processed images side-by-side, it highlights the importance of sophisticated image processing techniques in enhancing the functionality and accuracy of RTK GPS systems.

(a) (b)

Fig. 15. (a) Image Input of edge-of-row detection and (b) Canny edge detection result [84]

Hough line detection is a method used to find straight lines in images, even when they are unclear or broken. It works by mapping image pixels to a parameter space and identifying clusters of points that represent lines [87]. While effective, this technique can be slow and sensitive to settings. Improved versions, like the Probabilistic Hough Transform, are faster and more practical [73], [74]. After finding lines, they need to be cleaned up to remove false detections. This involves filtering based on length, angle, and other criteria [87]. The final result is a set of accurate lines, which can be visualized as shown in Fig. 16 (a) [87]. It shows the results of applying the Hough Line detection algorithm on an image, where distinct lines are identified and marked. This visualization is essential for understanding how the algorithm isolates and enhances structural features in images. Advanced algorithms like Random Sampling and Consensus (RANSAC) are often used to improve the accuracy of line detection by effectively managing outliers and incorrect detections. The main objective of line filtering is to ensure that the detected lines accurately represent the relevant structures in the image, leading to more precise results for further analysis [84]. After line filtering, median filtering is a useful step for enhancing image quality. This non-linear technique is particularly effective at reducing impulse noise, such as salt-and-pepper noise, without blurring edges. The process involves using a sliding window approach, where the central pixel is replaced by the median value of the pixel intensities within the window. This method preserves important edge information and is robust against outliers, ensuring that extreme pixel values do not skew the results. Median filtering is widely used in various image processing tasks, such as medical imaging and computer vision, to create cleaner, more reliable images for further analysis or visualization. The choice of window size is crucial, as larger windows provide more smoothing but may blur fine details [88], [89]. Fig. 16 (b) shows image post-application of a median filter, which is used to reduce noise and improve the clarity of detected lines. This step is crucial for refining the output and enhancing the accuracy of line detection. Fig. 16 showcases the steps involved in refining image analysis for navigation purposes, such as detecting rows in agricultural fields. It displays both intermediate and final processing results using techniques like Hough Line detection and median filtering. This figure highlights how these image processing methods enhance the accuracy of machine vision when integrated with RTK GPS, clearly

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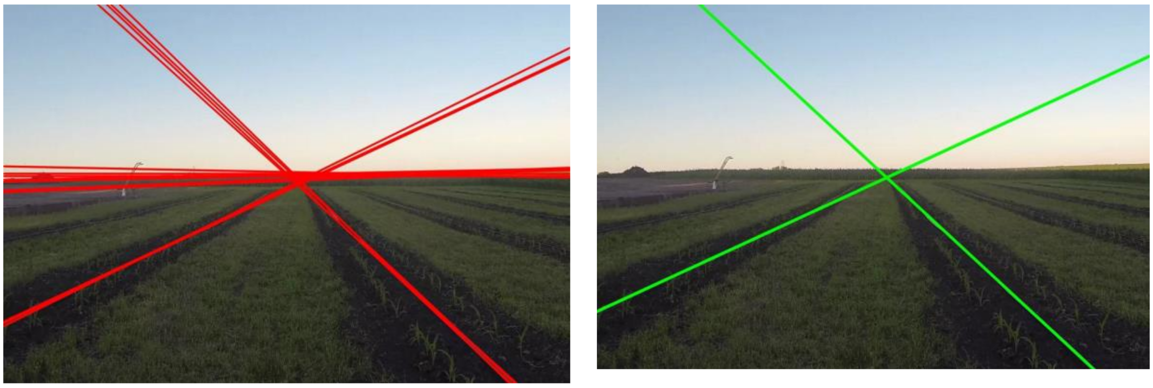
demonstrating their practical application and importance in achieving precise navigation in real-world scenarios.



(a) (b)

Fig. 16. (a) Hough line detection result and (b) Median filter result [84]

5. Proposed Method

The proposed system represents a crucial advancement over previous methodologies by incorporating the capability to localize defects on solar panels, a feature that was lacking in earlier works. Previous approaches primarily focused on defect detection without the ability to pinpoint the exact location of these defects within the solar farm, posing significant challenges for large-scale operations where precise maintenance is critical [90], [91]. Fig. 17 shows the new proposed method.

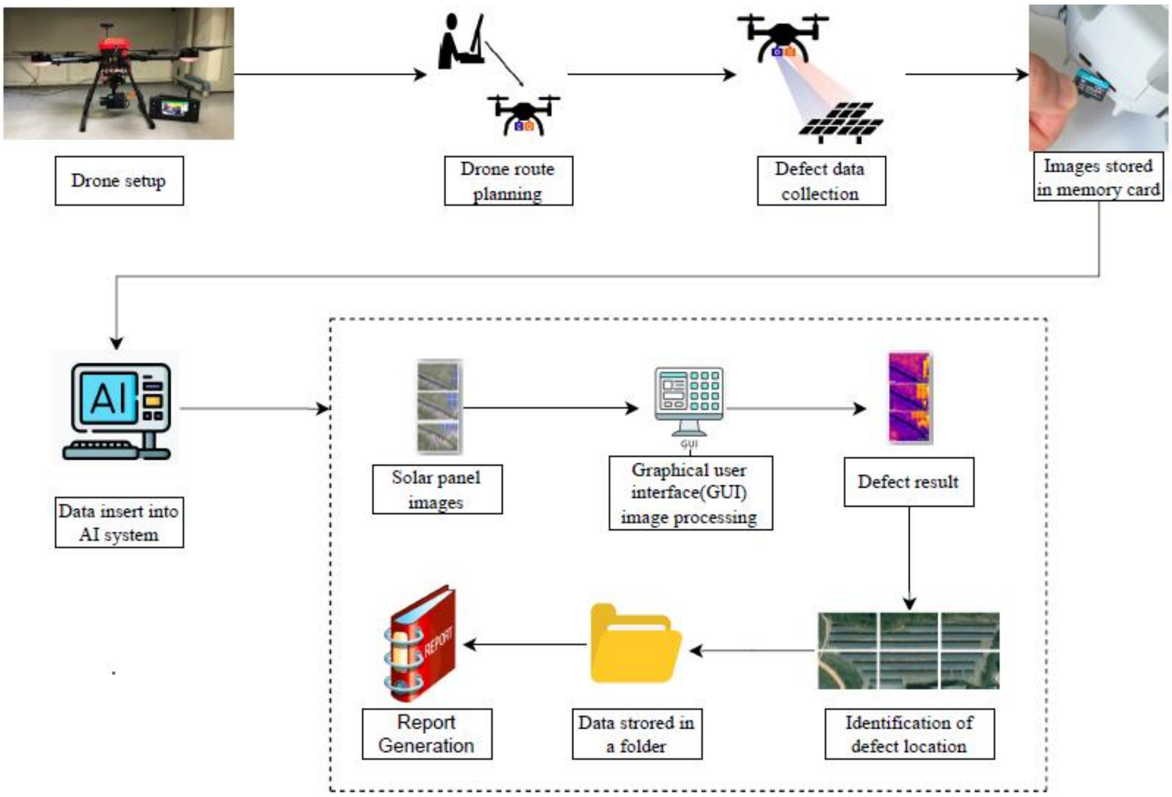


Fig. 17. Proposed method

The new proposed method enhances the efficiency and effectiveness of monitoring and maintaining extensive solar panel arrays by integrating advanced drone technology equipped with RTK GPS. The process begins with the careful setup of the drone, ensuring it is equipped with high-resolution cameras and thermal imaging capabilities. Utilizing Drone Harmony for route planning, the drone autonomously navigates across the solar farm, systematically capturing both standard and thermal images of the panels. This methodical data collection ensures comprehensive coverage without manual intervention. Once the images are captured, they are stored on a memory card and subsequently transferred to an AI system specifically designed for hotspot detection. This sophisticated AI system analyzes the images to detect any defects, such as hotspots, and crucially, identifies the exact location of these defects on the solar panels. The integration of RTK GPS allows for pinpoint accuracy in locating defects, significantly simplifying the process of targeting specific panels for maintenance. After processing, the data, including images, defect identifications, and their precise locations, are organized and stored in a designated folder. This structured data repository facilitates easy access and retrieval, enabling efficient report generation and follow-up actions. Such a system is especially beneficial in large solar farms where quick identification and remediation of defects are essential to maintain high levels of efficiency and prevent prolonged downtimes. This integrated approach not only surpasses the capabilities of previous methods in terms of defect detection but also introduces a novel aspect of localization, greatly enhancing the operational management of solar energy installations.

6. Conclusion

The review focuses on deep learning, drones, and thermal sensors to highlight current advancements in solar panel flaw detection. It talks about how features like concurrent feature extraction and weight sharing have increased the efficiency and accuracy of fault diagnosis. CNNs are known to provide superior generalization with less trainable parameters and to be more scalable than conventional neural networks [29]. A wider spectrum of flaws, including hotspots and cell failures, which each call for detection techniques, are also covered in the review. The application of thermal sensors is highlighted as a potential method for comprehensive flaw identification, especially when combined with drones. Cracks are a prevalent problem in solar panels and can be found with infrared imaging and thorough visual inspections. Nonetheless, there are still issues to be resolved, such as vanishing gradient issues with RNNs and handling lengthy sequences [92]-[94]. Even though these developments are significant, more research is still required to solve current problems and improve techniques. The need for continued innovation in the field of solar panel fault detection is critical. Thermal sensors, coupled with drone technology, provide a comprehensive method for identifying defects, but they are not without limitations. The resolution constraints and environmental sensitivities of thermal imaging require careful calibration and may incur significant costs [54]. Integrating drones poses its own set of challenges, including limited flight times and data processing delays, which can complicate the rapid assessment of large solar farms. Researchers and industry practitioners are encouraged to collaborate on developing more robust deep learning models that can process increasingly complex data sets from advanced sensor technologies. Furthermore, investment in adaptive learning systems could enable more proactive maintenance strategies, ultimately extending the lifespan of solar installations and reducing operational costs. Addressing the limitations in current solar panel fault detection, future research could investigate the integration of spectral imaging techniques with existing convolutional neural network models [20]. This approach may enhance the ability to identify subtle defects that are not readily apparent in standard RGB imagery. Additionally, leveraging advancements in unsupervised learning algorithms could facilitate the identification of previously undetected defect patterns, without relying on extensive labeled datasets. Such innovations have the potential to revolutionize the early detection of faults in remotely located solar installations. To sum up, research indicates that the combination of deep learning, thermal sensors, and drone technology is revolutionizing solar panel fault detection and creating a reliable, accurate, and automated solar energy system inspection system [5], [95].

To effectively address the identified shortcomings and advance the field, future research should focus on refining deep learning models and expanding their capability to process complex datasets from advanced sensors. There is a promising avenue in exploring spectral imaging integration with

CNNs to detect subtle defects not visible in standard imaging. Additionally, advancements in unsupervised learning algorithms could revolutionize defect identification without extensive labeled datasets, facilitating earlier and more accurate defect detection. The review culminates in a strong advocacy for ongoing innovation and collaboration among researchers and industry practitioners to drive forward these technologies in solar panel fault detection. This review significantly advances our understanding of defect detection technologies by highlighting the effectiveness of integrating CNNs with aerial surveillance technologies and localization. This review demonstrates the compounded benefits of integrating multiple advanced technologies, providing a holistic approach to tackling the challenges in solar panel maintenance. Table 1 provides a comparative summary of the research on defect detection technologies in solar panels, underscoring the need for a multi-faceted approach that incorporates both proven and novel methods to tackle the evolving challenges in the field.

Table 1. Comparative Summary of Research on Defect Detection Technologies in Solar Panels

Author(s)	Year	Thermal Imaging	Deep Learning	Methodology	Findings / Contributions
Kaldellis et al.	2022	✓		Used thermal imaging for defect detection focusing on hotspot and soiling defects.	Demonstrated the impact of soiling on panel efficiency.
M. Waqar Akram et al.	2022	✓		Reviewed failures of photovoltaic modules and detection methods.	Highlighted the necessity for effective detection technologies.
N. Padmavathi et al.	2017			Developed a fault detection system for solar panels using Bluetooth technology.	Enhanced remote monitoring capabilities.
J. Ahmad et al.	2021	✓		Applied frequency modulated thermography for detecting deep defects in steel, applicable to solar panels.	Improved detection of subsurface anomalies.
G. Li et al.	2022	✓		Conducted experimental research on welding defect detection using thermal imaging.	Applied thermal imaging techniques to detect defects.
S. Nylund and Z. Barbari	2019	✓		Studied defects in PV modules using UV fluorescence and thermographic photography.	Provided insights into defect characteristics and their detection.
J. Huang et al.	2023	✓	✓	Developed a solar panel defect detection design using the YOLO v5 algorithm, integrated with thermal imaging data.	Showed effectiveness in identifying and classifying panel anomalies with high accuracy.
H. K. Jung and G. S. Choi	2022		✓	Improved YOLOv5: Efficient object detection using drone images under various conditions.	Enhanced the ability to detect defects in challenging environmental conditions.
M. Hussain	2023		✓	Reviewed developments from YOLO-v1 to YOLO-v8, focusing on its application in digital manufacturing and industry.	Discussed the evolution and efficiency of YOLO algorithms in defect detection.
Mrs. N. Padmavathi & Dr. A. Chilambuchelvan	2017			Fault Detection and Identification of Solar Panels using Bluetooth	Proposed a novel approach for remote fault detection in solar panels using Bluetooth technology.
J. Ahmad et al.	2021	✓		Frequency Modulated Independent Component Thermography	Explored deep defect detection capabilities in steel samples, potentially applicable to solar panels.
M. Li et al.	2022	✓		Experimental Research on Welding Defect Detection Based on Thermal Imaging	Applied thermal imaging to detect welding defects, demonstrating its utility for solar panels.

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