

**DEEP LEARNING SYSTEM FOR IDENTIFICATION
AND CLASSIFICATION OF SOLAR
PHOTOVOLTAIC PANEL DEFECTS**

BY

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In

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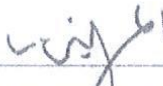
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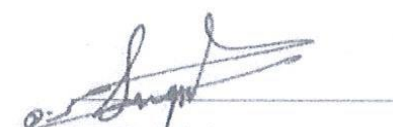




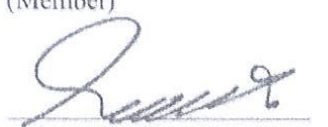
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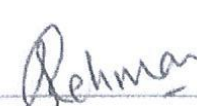
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Dedication

I dedicate this thesis to my parents, who provided unwavering support and encouragement throughout my academic pursuits. Their care, advice, and willingness to make sacrifices have motivated my accomplishments. Thank you for inspiring and pushing me to reach my full potential.

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LIST OF ABBREVIATIONS

Acc: Accuracy
CST: Concentrated Solar Thermal
C3: Cross-Context Convolutional
CSP-Darknet: Cross stage Partial Connection
DETR: Detection Transformer
DL: Deep Learning
E-ELAN: Efficient Layered Attention Network
EL: Electroluminescence
ELPV: Electroluminescence Photovoltaic
FCN: Full Connected Network
FP: False Positive
FN: False Negative
GIoU: Generalized Intersection Over Union
GW: Gigawatts
ILSVRC: ImageNet Large Scale Visual Recognition Challenge
Infra-Red: IR
IRENA: International Renewable Energy Agency
IR: Infra-Red
IoU: Intersection Over Union
mAP: Mean Average Precision
mAR: Mean Average Recall
ML: Machine Learning
MLP: Multi-Layer Perceptron
MSA: Multi Head Self-Attention
NIR: Near Infra-Red
NLP: Natural Language Processing
NIR: Near Infra-Red
NMS: Non-Maximal Suppression
OS: Operating System
PVS: Photovoltaic System
PVEL-AD: Photovoltaic Electroluminescence Anomaly Detection
PV: Photovoltaic
PPYOLOE: PaddlePaddle You Only Look Once Efficient
ResNet: Residual Network
RCNN: Region-based Convolutional Neural Network
RGB: Red Green Blue
SC: Solar Cell
SENet: Squeeze-and-Excitation Network

SM: Solar Module
SP: Solar Panel
SWIR: Short Wave Infra-Red
TEC: Thermoelectric Cooling
Vit: Vision Transformer
TP: True Positive
TN: True Negative
YOLO: You Only Look Once
YOLOS-PV: You Only Look at One Sequence Photovoltaic
YOLOS: You Only Look at One Sequence
YOLOR: You Only Learn One Representation,
YOLOX: You Only Look Once X

ABSTRACT

Full Name : Tella, Hambal Babatunde
Thesis Title : Deep Learning System for Identification and Classification of Solar Photovoltaic Panels Defects
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This thesis focused on detecting defects of solar panels in a solar photovoltaic plant using deep learning models. Solar panels represent a component in the plant which are vulnerable to defects caused by various weather conditions and posing challenges for effective maintenance. Traditional visual inspection methods used for defects identification are often inadequate, especially in large installations. Hence, specifically, the study involves the segmentation of solar panels from the background in photovoltaic systems using SegFormer model. Then, the application of six YOLO variants models were applied on the defective and non-defective panels dataset. Among the YOLO variants, the YOLOS model demonstrates better performance, and further optimization is achieved through adjusting weights of the networks, giving the YOLOS-PV model.

Further to the panel's defects, the research investigates the application of twelve deep learning models to classify defects of solar cells. By leveraging electroluminescence phenomenon, these models prove to be more effective in defect classification. In summary, this work experimented the use of deep learning models for defect detection in solar panels and extending to defects classification in solar cells.

ملخص الرسالة

الاسم الكامل: تيّلا ، حنبل باباتوندي

عنوان الرسالة: نظام التعلم العميق لتحديد وتصنيف عيوب الألواح الشمسية الكهروضوئية

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ركزت هذه الأطروحة على اكتشاف عيوب الألواح الشمسية في محطة الطاقة الشمسية الكهروضوئية باستخدام نماذج التعلم العميق. تمثل الألواح الشمسية مكونا في المصنع عرضة للعيوب الناجمة عن الظروف الجوية المختلفة وتشكل غالبا ما تكون طرق الفحص البصري التقليدية المستخدمة لتحديد العيوب غير كافية ، خاصة .تحديات للصيانة الفعالة ومن ثم ، على وجه التحديد ، تتضمن الدراسة تجزئة الألواح الشمسية من الخلفية في الأنظمة .في المنشآت الكبيرة على مجموعة **YOLO** بعد ذلك ، تم تطبيق ستة نماذج متغيرة . **SegFormer** الكهروضوئية باستخدام نموذج أداء أفضل ، ويتم **YOLOS** ، يوضح نموذج **YOLO** من بين متغيرات .بيانات اللوحات المعيبة وغير المعيبة بالإضافة إلى عيوب **YOLOS-PV**. تحقيق مزيد من التحسين من خلال ضبط أوزان الشبكات ، مما يعطي نموذج من خلال الاستفادة .اللوحة ، يبحث البحث في تطبيق اثني عشر نموذجا للتعلم العميق لتصنيف عيوب الخلايا الشمسية باختصار ، جرب هذا العمل .من ظاهرة التلألؤ الكهربائي ، تثبت هذه النماذج أنها أكثر فعالية في تصنيف العيوب استخدام نماذج التعلم العميق للكشف عن العيوب في الألواح الشمسية والتوسع في تصنيف العيوب في الخلايا الشمسية

CHAPTER 1

INTRODUCTION

There are two main categories of solar power plants: solar Photovoltaic (PV) systems and Concentrated Solar Thermal (CST). PV system employs Solar Panels (SP) while (CST) technology converts solar thermal energy into steam that subsequently powers a turbine to generate electricity. Specifically, this thesis focuses on PV systems utilizing SP. PV systems are designed to harness energy from sunlight and convert it into electricity. These systems can be divided into two primary categories: off-grid (stand-alone) and on-grid (grid-connected) systems, and they can also function in a hybrid manner where both types are combined. The key difference between off-grid and on-grid is the connection and interaction with the electrical grid. Off-grid PV systems are frequently employed in isolated regions where access to the electrical grid is scarce or non-existent. These self-contained systems operate independently, generating electricity to fulfill the energy requirements of a specific location without relying on external power sources. Off-grid offers a crucial advantage in their ease of integration with several types of constructions, including industrial and residential buildings, to address their electricity demands. Architects suggest that off-grid PV system should replace structural elements such as walls, as opposed to simply laying SP on the building roofs, to generate electricity and offer structural support at the same time [1]. Off-grid electricity generation is facilitated by the abundance of solar radiation, making PV system a good option to integrate with new and existing structures like trains

and streetlights that also reduce carbon emission [2].

On the other hand, the global shift towards renewable energy sources has paved the way for the rapid growth of on-grid PV systems. They offer a sustainable and efficient solution for electricity generation without necessarily connecting to storage or batteries but to the utility grid. This ensures access to electricity even with the absence of solar radiation unless the grid goes down. Furthermore, it supports net metering, enabling users to balance their electricity usage by supplying excess energy back to the grid [3]. This bidirectional energy flow gives the grid-connected PV system more advantages in usability over off-grid. Similarly, further research in PV system shows that both grid-connected and off-grid can generate electricity at night by implementing the Thermoelectric Cooling (TEC) technique [4].

The PV system consists of multiple SP organized in arrays affixed to a supportive framework. Additionally, it comprises various other components, such as inverter, charge controllers, battery banks, transformers, and AC grid systems [5]. The performance of each of these components is closely monitored to ensure optimal distribution of the electricity generated to end-users. SP comprises of individual Solar Cells (SC) which is made up of layers of silicon, phosphorus, and boron. When photons are absorbed by SP, an electric current is generated by releasing electrons from atomic orbits into the electric field of the SC. This process is known as the Photovoltaic Effect. Typically, electrical connections between SP are created using conducting wires, which must be sized appropriately for the current rating and fault conditions. These cables are responsible for collecting the current from the SP. The SP are connected in a series configuration to attain the targeted output

voltage, and in parallel to attain the desired current capacity, measured in amperes. The series connection of SP form Solar Strings (SS) while the parallel connection of SP forms Solar Array (SA) in the PV system [6]. When one SP is removed from SS, the overall voltage of the string decreases. This is because SP in a string is typically connected in series, meaning the voltage across each panel adds up. Removing a SP in SA reduces the total current, but the voltage remains constant. Furthermore, while the terms Solar Module (SM) and SP often used interchangeably, sometimes, SM are known to be combined to form SP as shown in Figure 1 [7].

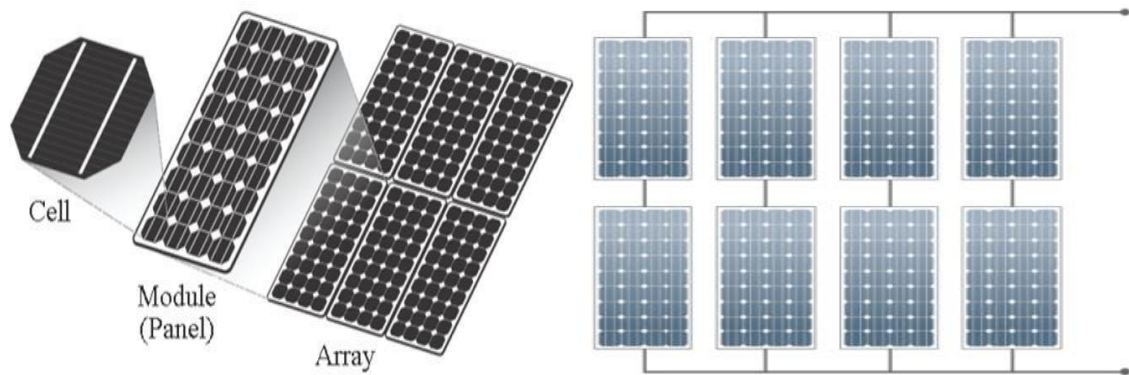


Figure 1: Photovoltaic System with SP displaying from SC to solar arrays [7]

The most used SP dimensions include the 60-cell, 72-cell, and 96-cell variations. The 60-cell panel, often arranged in a 6×10 configuration, has dimensions of 3.25 feet by 5.5 feet. Similarly, the 72-cell panel, organized in a 6×12 pattern, is 3.25 feet by 6.42 feet. On the other hand, the 96-cell panel, structured as an 8×12 arrangement, spans 41.5 inches by 62.6 inches.

1.1. Motivation

Photovoltaic (PV) systems are widely recognized as a prominent and efficient renewable energy solution. They play a crucial role in mitigating greenhouse gas emissions and contribute significantly to combatting climate change. One of the primary advantages of PV system is that they generate electricity without producing harmful emissions. PV system also offer long-term cost savings as they require minimal maintenance and have a lifespan of up to 25 years or more [8]. This facilitates the adoption of the systems for different applications. For instance, according to the International Renewable Energy Agency (IRENA), global renewable energy generation capacity has experienced a remarkable growth from 40 GW to over 3,000 GW over the last ten years [9]. Concurrently, solar power generation costs have plummeted by approximately 80% within the same period. Aligned with the Saudi Arabia Vision 2030, projections indicate that the region's solar power electricity generation is expected to achieve 40 GW, accounting for half of the total power generation capacity in the Kingdom. To achieve this, the SAKAKA solar power project, which features 1.2 million SP, was launched in November 2019, and has already contributed around 300MW powering about 44,000 houses [10]. Additionally, ACWA Power is collaborating with twelve domestic and international partners to set up seven new projects, which would add 4.55 GW of solar power generation to the Kingdom's power capacity. This trend underscores the region's dedication to generating electricity from solar power plants, given the widespread availability of solar radiation sources. Hence, the need to embark on profound research work on any condition that could reduce the performance of the generation of electricity from solar power plant.

1.2. Problem Statement

Solar power is rapidly becoming a more usual form of renewable energy around the globe. With the increasing demand for clean energy sources, SP has become a popular method of generating electricity, especially in sunny regions. However, despite the many advantages of SP, there are still some challenges associated with this technology. One significant challenge is their inability to generate efficient power during cloudy or rainy days. This factor limits the consistency of their output and calls for backup systems to supplement their power. While the installation of battery storage systems has been developed over the years to mitigate these issues, it still requires further research and development to make it more reliable and cost-effective.

Another obstacle faced by SP, particularly in urban areas, is the poor absorption of sunlight. The coverage of tall buildings, particularly in densely populated areas can reduce the amount of sunlight absorbed by the panels, thus limiting their effectiveness. The positioning of SP at ideal angles and locations can significantly impact their effectiveness.

However, a significant limitation of SP is their dependency on sunlight to generate electricity, even though there has been progress in research towards this problem by generating electricity at night through the method known as TEC. Since SP are usually situated outdoors due to dependency on sunlight, they are exposed to different sorts of weather conditions like rain, humidity, and wind. While SP are designed to withstand unfavorable weather conditions, certain weather conditions can significantly affect their efficiency. For example, cloudy and rainy weather can reduce the amount of sunlight

radiation that the SP absorbs, thus reducing the amount of electricity they generate. According to a study by the National Renewable Energy Laboratory, SP can experience a reduction in energy output by up to 50% during cloudy weather conditions [11]. Furthermore, severe weather conditions like hail, snow, intense winds, and even temperatures exceeding the standard sunlight radiation of $1,000 \text{ W/m}^2$ can result in damage to SP. Hail can cause physical damage, while snow can cover the surface of the SP, reducing the amount of sunlight radiation that they absorb. Intense winds can cause the SP to shift or break, affecting their efficiency. Hence, to mitigate the effect of extreme weather conditions and other factors such as manufacturing and installation issues on the SP, a few techniques have been used and the most common one has been manual checking by experts. This is costly and time consuming, especially for commercial solar plants that could have millions of panels on the field. To address this, we proposed a drone-based inspection that will survey millions of SPs with embedded thermal camera for easy detection of the defective part.

1.3. Research Objectives

Given the difficulties that SP encounters in generating electricity, these challenges could become worse if appropriate mitigation measures are not implemented to address them. The approach used involved utilizing deep learning models to classify and detect potential defective regions. There are two scenarios for managing these challenges which are based on either large solar power plants or also for the manufacturers who can replace the SC. Since the lowest component of the SP is the SC in which, if a particular SP is faulty, the manufacturer will get the root cause by changing or repairing the SC. This made it possible

for us to investigate the SC for defects when SP have been exposed to harsh weather and the efficiency has reduced. So, the research focuses on classifying the SC defects using deep learning models on the electroluminescence images.

However, many plants consist of several millions of SP and repairing or removing SC will be tedious and not encouraging. Hence, the project focused on segmenting and detecting the defective SP on the PV system. With this, it is easier for consumers to replace the defective SP and if possible, could send it to the manufacturer for repairing. This is the most used technique by the consumers for residential SP. In detecting the defects in SP, two fundamental architectures were used which are CNN and Transformer. These architectures are the building blocks behind the variants of object detection models known as You Only Look Once (YOLO) and segmentation models which were conducted on the solar thermal images. The description of the fundamental models is given below:

1. Convolutional Neural Network

Convolutional Neural Networks (CNNs) are deep learning models primarily used for computer vision tasks, although they have been applied to other domains as well. They are particularly effective at processing grid-like data, such as images and, more recently, sequential data like time series and natural language [12]. The component of CNN includes the following:

- i. Convolutional Layers: CNNs use convolutional layers to automatically learn hierarchical patterns and features from input data. These layers are called hidden layers as shown in Figure 2. They apply a set of learnable filters

(kernels) to the input data, sliding them across the input in a systematic way to create feature maps. Each filter captures several aspects of the data, such as edges, textures, or more complex structures.

- ii. Pooling Layers: After convolutional layers, pooling layers are often used to downsample the feature maps or extracted image information and reduce their dimensionality. This helps in reducing computation and makes the network more robust to variations in input data.
- iii. Fully Connected Layers: After several convolutional and pooling layers, CNNs often have one or more fully connected layers at the end. These layers flatten the feature maps into a vector and feed it into a standard neural network for classification.

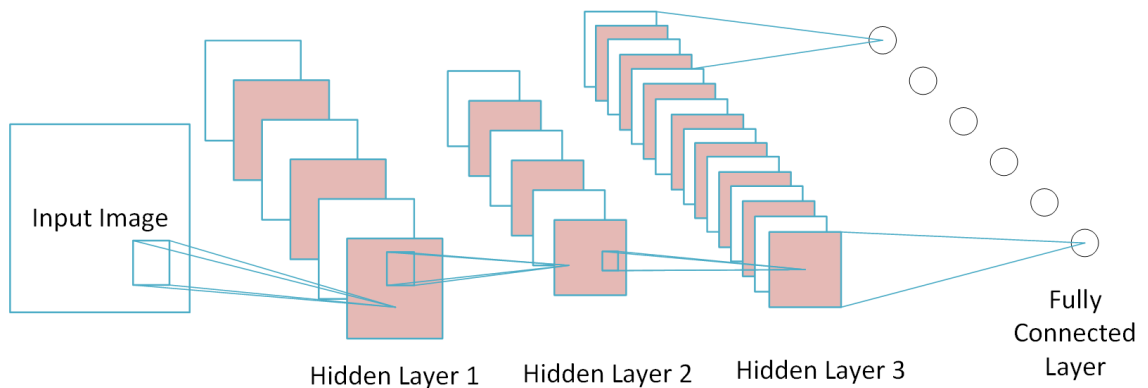


Figure 2: Architecture of a Convolutional Neural Networks

2. Transformer

Transformers are also a type of deep learning model initially designed for natural language processing tasks. However, they have been applied successfully to various other tasks like image processing that facilitate the use of the transformer

in this research work. Also, they gained prominence due to their ability to manage sequential data efficiently and have a self-attention mechanism that captures dependencies between elements in the sequence as shown in Figure 3. The component of transformer includes the following:

- i. Self-Attention Mechanism: it is used to weigh the importance of different elements in the input sequence when processing each element. This allows them to capture long-range dependencies and relationships within the data.
- ii. Multi-Head Attention: Transformers often employ multiple attention heads in parallel, allowing the model to focus on several aspects of the input sequence simultaneously. This enhances the model's ability to capture several types of dependencies.
- iii. Positional Encoding: Since transformers don't inherently have a built-in sense of order in the input data (unlike CNNs, which process data in a grid-like structure), they use positional encoding to provide information about the position of each element in the sequence [13].

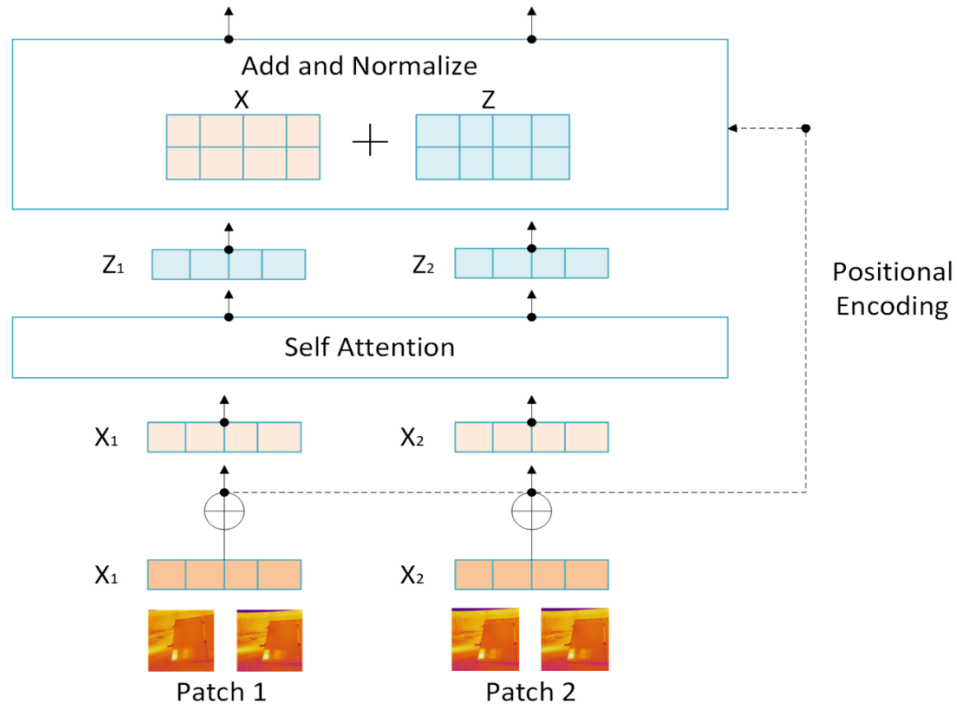


Figure 3: Transformer architecture for image patches inputs. The patches are converted to arrays of X_1 and X_2 where positional encoding is applied before transferring into the Self Attention. The output arrays from Self Attention are also other arrays of Z_1 and Z_2 .

In addition, questions that is aimed to be answered and achieved in this research work include the following:

1. Among the various deep learning model such as SENet, AlexNet, GoogleNet, ResNet, Exception, and SqueezeNet, which one exhibits the highest performance in effectively classifying SC defects?
2. Also, how accurately can the selected deep learning model classify the most common types of defects found in SC?
3. Can the classification accuracy of the selected deep learning model be improved by strategically tuning its hyperparameters or combining two or more models?
4. Since SP are usually captured by drone alongside the background, it is necessary to use a deep learning model such as SegFormer model for

segmenting the SP from the background. So, what type of segmenting model will perform best and its effectiveness.

5. Also, in detecting SP defects, a detection model such as YOLO was used. What is the effectiveness of the YOLO variants model in detecting several defects in photovoltaic panels?
6. Similarly, how does the accuracy of the YOLO models compare to other defect detection methods in identifying common types of SP defect.
7. Additionally, how can the YOLO model be fine-tuned to enhance the accuracy of detecting specific SP defects like junctions or hotspots? Is it viable to implement the YOLO model in practical situations, such as detecting defects in SP within extensive solar power installations?

1.4. Organization of the Thesis

The introduction chapter gave background knowledge on the PV system. It also includes the research problem, with research questions and objectives. Likewise, the chapter discussed the significance and motivation behind choosing the selected topics. Chapter two consists of an overview of existing research work on SP defects detection and SC defects classification using deep learning models. The chapter discussed the performance evaluation metrics to measure how accurate the model performs for the given selected dataset. It also discussed the gaps in the research that the thesis addressed with relevant theories and concepts. The research methodology chapter comprises of two sections starting off with the descriptions of the data collection and preprocessing. Then, the deep learning architecture used that includes the description of the method while applying the

models. This chapter also talks about the analyses of the performances and comparison with the existing methods. It also discussed the possible practical applications of the developed methods in the solar energy industry. The conclusion chapter encompasses recommendations for future research and discussion of the implications of the study findings and offers a summary of the research questions and outcomes. The thesis also includes appendices that provide comprehensive insights into code implementation details, theoretical research advancements, and platform implementation comparisons.

CHAPTER 2

LITERATURE REVIEW

Solar Photovoltaic (PV) system fault detection traditionally requires expert intervention and detection through conventional methods such as thermal and electrical modeling [14]. These methods focus on analyzing temperature and power output of the panel to identify performance behavior. Despite the use of advanced thermal techniques, these conventional methods are insufficient in detecting SP or classifying SC defects like cracking, hotspot, or soiling. However, deep learning techniques can identify and classify these defects, making them a viable approach.

The use of deep learning models has been experimented to detect SP and classify SC defect with the help of images captured by drones using thermal imaging camera for SP and electroluminescence camera for SC. The process of electroluminescence encompasses passing currents through the SC, resulting in the emission of weak Infrared (IR) light. This emitted light can be captured using specialized IR cameras known as EL cameras. The captured image data is collected and employed to train deep learning models for the purpose of defect classification in SCs.

2.1. Background

This section includes the background description of SCs and SPs that aids in understanding the reviews. It also includes the description of the approaches in detecting and classifying defects in SP.

2.1.1. Solar Photovoltaic Panel

The SP comprises of array connection of SCs. This has three common cell array configurations which are 60-cell, 72-cell, and 96-cell as shown in Figure 4. The 60-cell and 72-cell are the standard for commercial and resident that generate about 160 Watts to 300 Watts at 36 Volts depending on the type of cell [15]. The SP is mostly encapsulated with tempered glass (or other transparent materials) on the front surface and with protective and waterproof materials on the back surface. At the back of the panel, there is a junction box or wire leads providing electrical connection between the SC and the external wires. This also contains a bypass diode that prevents reverse current flow and minimizes power loss due to shading or other obstructions. The junction box protects the wiring from environmental conditions, such as moisture and debris, and ensures safe and reliable operation of the PV system.

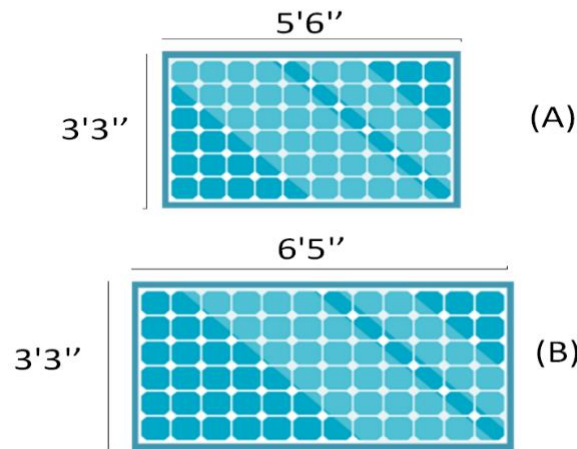


Figure 4: (A) 60-cells (10x6) and (B) 72-cells (12x6) type of SP.

One of the most common ways SP defects occur is through the exposure to unfavorable weather conditions like strong wind, snow, and dust. Although, the origin of these defects can vary, from manufacturing defects to installation issues or environmental factors.

However, the focus of the thesis is on the detection of the SP defects that occur frequently in the PV system like hotspot, soiling and cracking. Table 1 shows the different types of defects in SP that are due to the installation, environment, and manufacturers issues.

Table 1: Type of defects in SP by manufacturer, environmental conditions, and users.

No	Defect types	Possible Causes	Cells/Panels
1	Hotspot [14]	Extreme Temperature	Cells and Panels
2	Broken glass [16]	Hail or collisions	Panels
3	Dust Build up.	Strong wind or dust accumulation	Panels
4	Cracked back sheets.	Collision or other harsh environmental conditions	Panels
5	Ribbon Discoloration	Corrosion, heat, or moisture exposure	Panels
6	Encapsulant Discoloration	UV light exposure, hot temperature, and humidity	Panels
7	Delamination	Manufacturing, installation issues and Environmental conditions.	Cells and Panels
8	Bubbles	Inadequate heating, and moisture or contaminants.	Panels
9	Defective Junction box [17]	Faulty connections	Panels
10	Poor String Connection	Inadequate soldering, mechanical damage, or presence of debris	Panels
11	Potential Induced Degradation (PID)	Exposure to hot temperatures and humidity	Cells and Panels
12	Back contacts	Faulty connections of back contact	Cells and Panels
13	Corroded	Moisture or humidity and extreme temperature.	Cells and Panels
14	Soiling	Accumulation of dirt, dust, or other materials	Cells and Panels
15	Multi-Defects	Combination of the causes	Cells and Panels
16	Diode Defects	Installation and functioning of bypass diodes	Panels

Broken glass defect is caused in the front glass of a SP. It is the first line of defense against various environmental factors and could get damage due to factors such as hail or collisions [16]. This can expose the underlying SP to weather damage, making them more vulnerable and impacting the overall performance of the SP. Dust buildup defects or soiling are caused

by dust accumulation which can block solar radiation from reaching the SP and reduce their effectiveness, leading to lower power output. This is one of the most common defects that affect the efficiency of the SP. Similarly, we have crack backsheets that are based on the crack that occurs at the backsheets component. Backsheet is a key component of a SP and provides protection to the SP from various environmental factors. Cracks in backseats can allow moisture or other contaminants to penetrate the panel, potentially leading to corrosion or other damage that can affect the performance of the SP.

Ribbon discoloration presents another type of defect that can emerge within the cell interconnect ribbon of SPs. This issue can arise due to several factors including corrosion, heat, or exposure to moisture. Ribbon discoloration is often associated with reduced power output in the SP and can negatively impact its overall performance. Encapsulant discoloration defects is caused because of discoloration of the encapsulant layer that covers the SC and acts as a protective barrier. A defective junction box is a module defect in the PV system. The junction box is a key component of SP that provides a connection between the SP and the rest of the system. If the junction box is defective, it can cause reduced power output [17]. A SP consists of multiple SC that are connected in series or parallel depending on the electrical requirements of the system. A string of cells is formed by connecting multiple cells in series. Poor string connection can occur due to a variety of reasons such as inadequate soldering, mechanical damage, or presence of debris. It can lead to reduced power output and other issues in the SP.

The several types of SP defects used in this work are the Hotspot, Diode and Junction that are combined under a class of defective and non-defective. These defects are also the available dataset gotten from the public dataset repository.

2.1.2. Solar Photovoltaic Cell

A SC is an electronic device classified as a photoelectric cell that directly converts the energy of light into electricity through the PV effect. The PV effect means generation of voltage and electric current in a material upon exposure to light. The SC is also considered as photovoltaic regardless of whether the source of energy is natural sunlight radiation or artificial light. In addition to generating energy, they serve as photodetectors capable of sensing light or electromagnetic radiation within the near-visible range. Silicon is used as a semiconductor material in SC. The typical rating of silicon SC is 0.5 Volts and 6.0 Amperes which equivalently amount to 3.0 Watts power. These ratings are added together depending on the type of cells connections to form SP such as 60-cells or 72-cells in a SP. In identifying SC defects, as shown in Table 2, we have several types with the potential causes that are majorly manufacturing issues.

Table 2: Type of defects in SC by manufacturer, environmental conditions, and users.

No	Defect types	Possible Causes	Cells or Panels
1	Hotspot [14]	Extreme Temperature	Cells and Panels
2	Microcracks	Manufacturing defects or installation issues	Cells
3	Cracked Cells	Extreme temperature or collision	Cells
4	Snail Trails [18]	Collision	Cells
5	Delamination	Manufacturing, installation issues and Environmental conditions.	Cells and Panels
6	Potential Induced Degradation (PID)	Exposure to hot temperatures and humidity	Cells and Panels
7	Back contacts	Faulty connections of back contact	Cells and Panels
8	Edge Isolation	Faulty connection between the front and back contacts of an individual SC near the edges.	Cells
9	Fingerprint	Manufacturing and installation issues. Detected using MFI (Magnetic Field Imaging) [19]	Cells

10	Picker Print	Manufacturers from deposition technique, ink or paste quality, printing parameters.	Cells
11	Corroded	Moisture or humidity and extreme temperature.	Cells and Panels
12	Dark area [20]	Prolongation of low electroluminescence (EL) intensity along the cell adjacent to the shunt	Cells
13	Edge Shunt	Manufacturers	Cells
14	Soiling	Accumulation of dirt, dust, or other materials	Cells and Panels
15	Multi-Defects	Combination of the causes	Cells and Panels

Hotspots defects occur when a damaged or defective SC has a localized heating effect on its part. This heating effect can cause damage to adjacent cells and degrade the overall performance of the SP [21]. We used thermal imaging as one method that can help identify hotspots. It is a type of imaging technology that uses infrared cameras to detect and measure temperature variations in objects such as SP [22]. Microcracks are other types of defects that can occur at the cell level in SP. These small cracks are usually not visible to the naked eye but can impact the performance and efficiency of the PV system. Microcracks can be caused by several factors, including manufacturing defects or installation issues, and can be detected through specialized techniques like electroluminescence imaging. Cracked cells defects in SP can negatively impact the performance and efficiency of the cell. Cracks can cause a reduction in power output, reduced durability, and can also lead to issues like hotspots. Snail trails are defects that are usually visible as dark lines that run across the SC [18].

Potential Induced Degradation (PID) defect is a phenomenon where a high voltage potential is induced between the SC and its frame, leading to power loss in the SP. This can be caused by a variety of factors such as exposure to hot temperatures and humidity. In a SC, we have

back contacts that are used to collect the current generated by the cell and transfer it to the rest of the system. Similarly, we have back contacts for SP that connect the individual SC in the panel together to form a larger SP. However, poor quality back contacts or inadequate connections between the back contacts and the rest of the system can lead to reduced power output and other issues with the panel. Edge isolation defect occurred due to the edge isolation process. This is the process of removing the electrical connection between the front and back contacts of an individual SC near the edges to prevent electrical shorting between the cells. If edge isolation is not performed adequately, there can be issues such as short circuiting of the connection that led to reduced power output or even failure of the SP. Fingerprint and picker print defects are mostly caused by the manufacturers because of deposition techniques or ink quality. A dark area defect indicates regions of electrical inactivity or weakened diode performance. This occurs due to voltage drops and the extension of low electroluminescence (EL) intensity along the cell, particularly near the shunt [20]. In this thesis, an accumulation of a few defective SC's dataset was utilized from the list. Figure 5 shows the 11 SC defects used including a good cell. These are the publicly available defective SC classes gotten from literature.

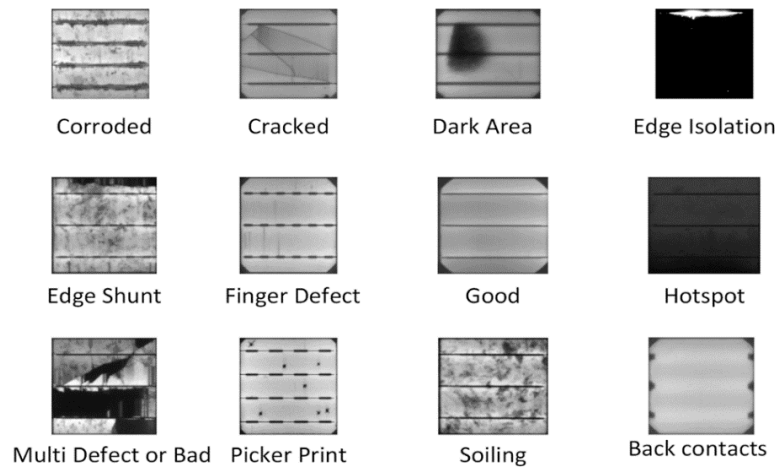


Figure 5: Sample SC defects identification consisting of 11 defects grey scale with non-defective cells.

2.1.3. Approaches for Detection and Classification of Defects in Solar PV Systems

There are two main steps required to identify the kind of defects in SP: the first approach is detecting the present of defects in a particular SP. The second step involves classifying the detected defects into several types of possible faults like hotspots and soiling.

In detecting defective SC/SP, we have different techniques such as:

1. Electroluminescence (EL) Imaging (SC defects) [20]
2. Infra-Red Thermal (IRT) Imaging (SP defects) [20]
3. Lock-in Thermal (LIT) Imaging (SP defects) [23]
4. Ultraviolet (UV) Imaging (SP defects) [24]
5. Magnetic Field Imaging (MFI) (SP defects) [25]
6. Spectroscopic Diagnostic Techniques (SP defects) [26]

Among these techniques, EL imaging is the only one used for SC defects while others are used for SP defect detection. These techniques are all non-destructive imaging techniques i.e., they do not destroy the sample image captured. Destructive and non-destructive imaging techniques refer to the methods of capturing images of samples which can structurally be affected [27]. Destructive techniques involve the damage of the sample or object, making it impossible to use it repeatedly for analysis. Examples of destructive imaging techniques, for instance are X-ray crystallography. This involves the destruction of a crystalline sample to obtain scattering data, or electron microscopy techniques that use electron beams to observe the sample. On the other hand, non-destructive methods allow for analysis of the object without altering or

damaging it, enabling the sample to be used repeatedly. Non-destructive imaging methods encompass X-ray imaging, thermal imaging, Lock-in thermal imaging, magnetic resonance imaging, and more. These techniques are especially crucial in various applications, including the detection of defects in SP.

Infrared Thermal (IRT) Imaging is a non-contact and non-destructive imaging method that employs infrared radiation to create an image depicting the temperature distribution of SP [20] as shown in Figure 6 (a). Electroluminescence (EL) Imaging is a non-destructive, effective, and commonly used method for identifying and locating defective sites on SC, such as cracks in the cells or connections, delamination, or shunts which can cause a degradation of the SP's performance or potential failure over time. The technique involves flashing an electrical current across the SC, which produces a measurable visible light. The visible light produced is proportional to the current flowing through the cells and can help identify regions where there is a reduced current flow or hotspots indicative of defects as shown in Figure 6 (b). The technique can be used for analyzing SC from a production line or for SP field inspections on-site.

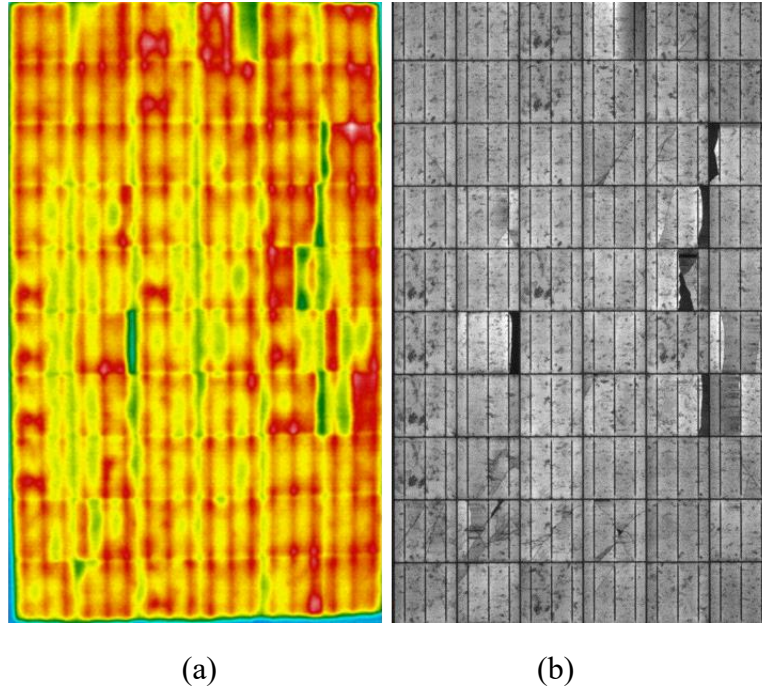


Figure 6: (a) Infra-Red Thermal (IRT) Imaging and (b) Electroluminescence Imaging [20]

Lock-in thermal (LIT) is also another non-destructive and non-contact thermal imaging technique that is widely applied for the detection of defects and failures in SP [23]. LIT is based on the concept of modulating light or heat to generate a thermal response in the panel's material, which can then be detected by an infrared camera. The thermal waves generated are analyzed by applying a lock-in amplifier that can isolate thermal waves at varying frequencies, allowing for the detection of localized areas in SPs with defects. LIT is suitable for identifying hidden faults in modules or wafers, delamination, residual stresses, and shunts on SP. While both LIT and IRT are thermal imaging techniques, they differ in their operating principles and resolution capabilities. In the context of SP, LIT is an advanced approach that can detect defects and local thermal variations with high resolution as shown in Figure 7 for a shunt defect detection. IRT is more commonly used

for detecting faults on SP, such as hotspots by measuring the temperature variations on their surface [28].

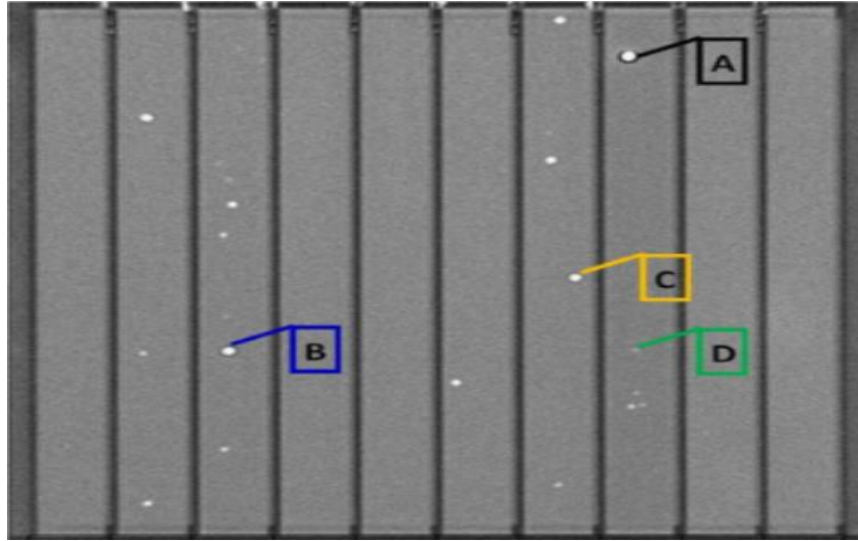


Figure 7: LIT imaging detection techniques for SP with shunt detections. Point A, B, C and D shows the different shunt defect detected [28]

Ultraviolet (UV) imaging can be used on SP to detect defects, such as cracks or delamination, by identifying localized changes in the surface temperature of the panel. UV imaging is achieved by exciting the sample with high-energy light and detecting the emission of fluorescent light. In the SP industry, UV excitation can be accomplished using a UV LED light source, which illuminates the panel and then captures the resulting fluorescence with an imaging system. UV imaging can reveal defects that may not be visible to the naked eye, such as microcracks, and can be a useful tool for quality control during the manufacturing process or for inspecting panels in the field. By identifying defective areas, corrective actions can be taken to prevent further damage and improve the energy output of the SP [24].

Magnetic Field Imaging (MFI) is also a non-destructive imaging technique that can be used to detect defects in SP [25]. MFI works by analyzing the magnetic field generated by the

electrical currents in the panel. The technique involves applying a magnetic field sensor to the surface of the panel, which then captures the changes in the magnetic field generated by the currents flowing through the panel. MFI can detect defects such as broken or poorly connected cells, which generate lower magnetic fields than normal cells.

Spectroscopic diagnostic techniques can also be used for SP detection to detect defects in a non-destructive way [26]. These techniques involve shining light on the surface of the SP and measuring the resulting radiation. By analyzing the spectrum of the radiation, defects can be identified and localized. However, these techniques may require specialized equipment and expertise, and they may have limitations in terms of sensitivity and resolution.

In this research work, none of these techniques were performed in the laboratories. The output of the techniques as performed by other researchers have been utilized. For instance, the EL techniques applied to some set of SCs have been used and downloaded from different repository sources. Classification techniques are then applied on these sets of datasets.

Classification techniques involves identifying each detected SC/SP defects with the help of classification methods like:

1. Deep Learning/Machine Learning
2. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [29]
3. Digital Signal Processing (Wavelet Transform and Fast Fourier Transform (FFT)) [30]

Many research studies have explored the application of deep learning models to analyze images of SP. For instance, one study introduced an automated method for classifying defects in photovoltaic (PV) systems using deep learning models [31]. In another study, the detection of defects in SP was tackled by processing thermal images captured through a thermal camera, employing deep learning [32]. Utilizing machine learning or deep learning within solar power technology entails an increment of SP efficiency and performance. This can include tasks such as predicting SP degradation, detecting defects or anomalies in images of SP, optimizing panel placement, and tracking, and predicting solar irradiance. Machine learning and deep learning models have proven highly effective within this domain due to their capacity to manage substantial datasets and progressively improve performance over time. Ongoing efforts are dedicated to applying for the classification of photovoltaic defects and developing machine learning-based models to optimize the operation and maintenance of solar energy systems. Machine learning relies on various models including neural networks, decision trees, and support vector machines. Nonetheless, deep learning methods exhibit better performance compared to machine learning approaches, particularly when dealing with large datasets. The use of extensive datasets enhances classification accuracy by accounting for the diverse nature of the data. Consequently, this makes deep learning architectures such as AlexNet, SENet, ResNet, GoogleNet, YOLO, and others well-suited models for the classification of defects in SP. In this thesis, we have adopted the use of deep learning models to classify the defects unlike the other techniques like Digital Signal Processing (DSP) and ANFIS. ANFIS, or Adaptive Neuro-Fuzzy Inference System, is a type of artificial neural network that combines the advantages of fuzzy logic and neural networks to make predictions based on input data.

Several studies have applied ANFIS for SP defect classification [29]. These studies demonstrated that ANFIS can classify SP defects, making it a promising approach for SP defects classification. However, this technique has limitation of loss of interpretability and lack of scalability with large inputs unlike deep learning. Likewise, classification techniques under DSP were proposed using wavelet transform and Fast Fourier Transform to classify the defects [30]. The techniques can help detect the defect in the image by segmenting the defective sections like crack in the SP as shown in Figure 8.

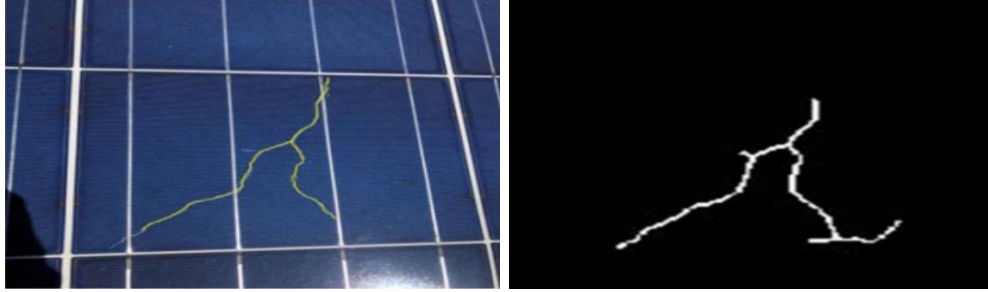


Figure 8: The segmentation of a crack defects in SP using Wave Transform and Fast Fourier Transform [30]

2.1.4. Performance evaluation metrics utilized in the literature

Performance metrics are measures used for evaluating the performance of a particular system or process. In this case, evaluating the models that are used for detecting defects in SC dataset or SP images. The research work in the literature is based on performance metrics commonly used for classification, segmentation, and detection models. Classification performance metrics encompass accuracy, F1 score, precision, and recall, categorized into micro and weighted averages as given in equation (1-5). Micro averaging involves global averaging across both samples and classes. Weighted averages are determined by calculating individual class scores, averaging them, and adjusting the weights based on the frequency of actual occurrences [33].

$$precision = \frac{TP}{TP+FP} \quad (1)$$

$$recall = \frac{TP}{TP+FN} \quad (2)$$

$$f_{1score} = \frac{2TP}{2TP+FP+FN} = 2 \times \frac{precision \times recall}{precision+recall} \quad (3)$$

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

$$balanced\ accuracy = \frac{recall+specificity}{2} \quad (5)$$

Where specificity is $\frac{TN}{TN+FP}$, True Positive (TP) indicates that a particular class of defects is accurately identified as present in the test set, while True Negative (TN) represents accurate identification of the absence of a specific defect. False Positive (FP) means wrongly identifying a defect that is not there. On the other hand, False Negative (FN) is when we mistakenly classify something as not being a specific type of defect even though it is.

The performance metrics used for segmentation tasks include mean accuracy and Intersection over Union (IoU) as shown in equation (6). Mean accuracy is a metric that calculates the average pixel accuracy across all classes in a classification task. It considers both correct and incorrect predictions and provides an overall measure of how well the model is performing on the entire dataset. IoU metric measures the overlap between the predicted bounding box or segmented region and the ground truth. The IoU is calculated by dividing the area of overlap between the two regions by the area of their union. Similarly, for detection of SP defects metrics, the metrics used are precision, recall, mean average recall and mean average precision at 50.0 and 50.0-95.0 confidence level or IoU threshold.

$$IoU\ (Segmentation) = \frac{TP}{TP+FP+FN} \quad (6)$$

2.2. Literature Review of SC/SP Defects Detection and Classification

This thesis focuses on SP defect detection and SC defects classification. In detecting SP, numerous Machine Learning (ML) models have been proposed. However, the prevailing approach in academic literature has focused on identifying defects using Red, Green, and Blue (RGB) images, rather than thermal images. Similarly, ML models can classify defective SC using the output image datasets from the EL imaging techniques. This dataset is known as elpv datasets [34].

2.2.1. SP Defects Detection

As part of this thesis work on detecting defects in SP, a thorough survey of relevant models and works on segmentation and object detection techniques for SP was conducted as shown in Table 3. The findings indicate that the focus of many studies has been on using aerial RGB images as a dataset for classifying defects. However, we discovered that successful defect identification in SP plants requires the use of detection techniques such as EL, IRT, LIT, UV, and MFI prior to the application of deep learning models, as described in [35]. This ensures better visibility and more efficient localization of defects. For instance, ResNet-34-based UNet segmentation models have been used in [36], to detect potential defects on aerial image rooftops and capture incoming solar radiation for optimal SP positioning. The model gave an accuracy of 77.0%. Likewise, [37] employed a deep learning model based on EfficientNet-B7 and U-Net segmentation to localize SP locations and their surface area on aerial satellite images obtained through the Static API from Google Maps, achieving an Intersection over Union (IoU) of 86.0%. In a similar vein, [38] developed a python package for solar segmentation that uses the Resnet-50 Feature

Pyramid Network (FPN) model to analyze satellite images [39], resulting in a mean Average Precision (mAP) score of 77.8%.

In [40], a segmentation model based on the ResNet-34 UNet model called RU-Net was introduced for segmenting aerial remote sensing images [41], achieving an Intersection over Union (IoU) score of 84.0%. In [42], three segmentation models - U-Net, RefineNet, and DeepLab v3+ were evaluated using satellite images with varying spatial resolutions containing SP. Mean IoU scores of over 85.0% were achieved. Similarly, [43] tested three segmentation models: U-Net, SegNet, and FCN on satellite RGB images, with accuracy of 94.7%, 94.1%, and 93.5%, respectively. In contrast, [44] employed other segmentation techniques such as image enhancement, line-segment detection, and k-means clustering to identify SP regions in an infrared RGB image dataset. The combination of these methods resulted in an SP segmentation model, denoted as SPS, with an F1 score of 86.0%.

Table 3: Summary of literature survey of SP defect detection

Authors	Tasks	Model(s)	Dataset(s)	Results
Soares et al. [36]	Segmentation	ResNet-34-based UNet	Aerial RGB Images (Unavailable)	77.0% (Acc)
Parhar et al. [37]	Segmentation	EfficientNet-B7 based. U-Net	Satellite RGB images downloaded from Google Maps (Unavailable)	86.0% (IoU) and 92.0% (mean F1 Score)
Perry et al. [38]	Segmentation	Resnet-50 FPN	Aerial RGB image (Available)	77.8% (mAP)
Li et al. [40]	Segmentation	ResNet-34-based UNet	Remote sensing RGB images	84.0% (IoU)
Jiang et al. [42]	Segmentation	U-Net, RefineNet, DeepLab	Satellite and aerial RGB dataset of	85.0% (mIoU)

		v3+	spatial resolutions of 0.1m, 0.3m and 0.8m (Available)	
Sampath et al. [43]	Segmentation	U-Net, Seg-Net, FCN	Satellite RGB images (unavailable)	94.7%, 94.1% and 93.5% (Acc) for UNet, SegNet and FCN.
Wang et al. [44]	Segmentation	Solar Panel Segmentation (SPS)	Infra-Red RGB image (Unavailable)	86.0% (F1 Score)
Tommaso et al. [45]	Detection	Yolov3	Infra-Red and Visible imaging by Drone (Unavailable)	70.0% (mAP@0.5)
Tajwar et al. [46]	Detection	Yolov3	Infra-Red Thermal images (Unavailable)	74.0% (Acc)
Zhu et al. [47]	Detection	TPH-YOLOv5	VisDrone2021, DET-test-challenge dataset (Available)	39.2% (AP) for DET-test-challenge and 39.4% (AP) for VisDrone2021
Pathak et al. [32]	Detection	faster RCNN	IR thermal Image (Unavailable)	67.0% (mAP)
Sun et al. [48]	Detection	YOLOv5	IR thermal Image (Unavailable)	87.8% (mAP), Average Recall of 89.0% (Ave Recall) and 88.9% (F1 Score)

RGB satellite images are unsuitable for detecting and classifying SP defects because they lack the necessary visibility [49]. This is why non-destructive detection techniques like IRT and LIT are applied before object detection models. For example, [45] used YOLOv3 object detection to analyze infrared and RGB images collected by a drone after undergoing IRT imaging techniques, while [46] used YOLOv3 only on IR images for hotspot defects

and RGB images for other defects. The $\text{mAP}@0.5$ score was 70.0%, and the confidence level for hotspot testing was 74.0%. Similarly, [47] proposed the TPH-YOLOv5 model, which builds on YOLOv5 by replacing the prediction head with Transformer Prediction Heads (TPH). This model was evaluated on drone RGB datasets from VisDrone [50] and DET-test-challenge, achieving average precisions of 39.2% and 39.4%, respectively. On the other hand, [51] used faster RCNN, known as edge detection models, for hotspot defect localization. This method achieved a mean Average Precision (mAP) of 67.0% when used with IR thermal images. [48] improved upon the YOLOv5 model by enhancing the anchor boxes and prediction heads, resulting in an AP-YOLOv5 variation that achieved a mAP of 87.8%, an average recall of 89.0%, and an F1 score of 88.9% on IR thermal images. In this work, we aim to bridge the gap in past studies detection and localization of SP defects by proposing the use of YOLO variants on thermal images, unlike RGB. We also introduce the YOLOS-PV model, which is based on the transformer YOLOS object detection model and propose an adjustment to the bounding box loss function consisting of L1 loss [52] and Generalized Intersection over Union (GIoU) [53] to a weight factor specific for detecting defects in solar thermal images.

2.2.2. SC Defects Classification

In a study by [54], the task of differentiating between normal and defective SC was addressed using a Support Vector Machine (SVM) classifier. This was accomplished using the elpv image dataset of 2,624 images. However, it is important to highlight that this dataset's classification is limited to four categories defined by probability values, and thus it does not encompass various other defects like corrosion or back contacts. Also,

considering the size of the dataset for training deep neural networks, which typically require larger datasets, the use of SVM was identified as a practical and suitable approach. The study showed that SVM outperformed other classifiers, such as KNN, Naive Bayes, Decision Tree, and ANN, achieving an accuracy of 97.5%. Additionally, in another study by [35], two different deep learning models, Inception-V3 and ResNet50, were employed to extract essential features from both binary (functional or severe) and multiclass (functional, moderate, mild, and severe) elpv datasets. As these models demand significant data volume, synthetic data were supplemented using data augmentation techniques that modify the size and angles of the original images. This augmentation approach expanded the training dataset, thus enhancing the models' efficiency.

Furthermore, SC defect datasets excluding the elpv dataset highlighted previously that encompass diverse defect classifications not covered, have been employed for the classification of SC defects. In [55], ResNet18 and YOLO-based models were trained using a set of 762 elpv images manually labeled for defects. Subsequently, these models were evaluated on a separate testing set containing 129 elpv images. The defects encompass cracks, intracell defects, intact-cell defects, oxygen-induced defects, and solder disconnections.

Similarly, deep learning models such as AlexNet, ResNet18, and YOLOv3 have been suggested for classifying defective SC, with better performance than SVM and KNN. Also, the combination of these deep learning models has shown more promising results in achieving higher accuracy performance when compared to a single deep learning model. According to [35], two different fused deep learning models (Inception-V3 and ResNet50) were used for SC defect detection of elpv images. The study indicated that the hybrid model

achieved a higher accuracy performance of 61.2%, outperforming the individual performances of 52.7% for ResNet50 and 48.4% for Inception-V3. In [56], a YOLO-based model called YOLO-PV was utilized on the elpv images dataset of 2,624 and produced an average precision (AP) of 94.6%, a significant improvement over the 78.0% AP achieved in [55] using the regular YOLO model. In line with the deep learning models performance on the elpv image dataset, ensemble techniques were applied to the dataset using multiple models, as suggested in [57]. It was found that utilizing the same number of models as the number of classes was the ideal approach for achieving optimal accuracy performance. Therefore, these models could potentially be applied in broader applications by leveraging ensemble techniques which was experimented in this thesis.

2.3. Research gap from the previous work

The following highlights the limitations of the previous methodology for SP defects detection.

1. Application of deep learning models for detection of SP defects in RGB Images:

In this research, deep learning models were employed to detect defects in SP using solar thermal images unlike RGB used in the literature. These models are designed to detect defects in SP's visual representations. The research leverages a dataset containing solar thermal images for the purpose of defect detection. Solar thermal images provide valuable data for understanding and identifying defects in SPs, as they capture the temperature variations and patterns that may indicate issues with panel efficiency or performance.

2. Lack of synchronization techniques among researchers: This research gap

highlights an issue in the SPs defects detection research community where different researchers or research groups use varying techniques, models, and datasets for similar tasks. For instance, two different research papers employing different deep learning models (e.g., convolutional neural networks, recurrent neural networks) on distinct datasets to address the same problem. This lack of standardization can make it challenging to compare and generalize results effectively. Standardizing methodologies and datasets can promote better collaboration and enable more reliable comparisons between different studies.

3. The dataset size discrepancy in deep learning models: One challenge faced in the application of deep learning models to SP problems is the size of available datasets. Often, deep learning models require large amounts of data for effective training and generalization. In the context of SP defect detection, the datasets available in the literature are relatively insignificant compared to the capacity and complexity of deep learning models. Limited dataset size can lead to overfitting (where models perform well on training data but poorly on new data) and hinder the ability of models to generalize to real-world scenarios. This is addressed in this research work where datasets are collected from various sources for better generalization of the deep learning models.
4. Lack of concentration on model improvement: Many research efforts in the field of deep learning and SP defect detection have focused primarily on applying existing models. This can lead to a gap in terms of model improvement and innovation. Instead of advancing the state-of-the-art models, researchers applied the models without optimizing or customizing them for the SP defect applications.

To address this, it is important for researchers to not only apply existing models but also work on refining and enhancing these models to achieve better performance and practical applicability.

CHAPTER 3

SOLAR PANEL DEFECT DETECTION

The widespread adoption of solar plants for energy generation has brought attention to the need for efficient defect detection techniques of SP. Defects such as cracks, diode, junction box and hotspots can reduce the efficiency of SP, resulting in energy losses. Deep learning, a branch of artificial intelligence, has shown immense potential in defect detection through its ability to learn complex patterns from images.

This study explores the application of deep learning models to detect defects in SP. By training deep neural networks on annotated datasets of defective and non-defective panels, accurate and efficient models for defect detection were developed. The use of deep learning promises rapid and consistent detection of defects, outperforming other techniques. This research contributes to the advancement of solar energy technology by ensuring the reliability and longevity of SP, thus enhancing the overall sustainability of clean energy generation.

3.1. Dataset Collection and Preprocessing

To develop and train effective deep learning models for SP defect detection, a comprehensive dataset is essential. This section explains how the dataset was collected and preprocessed. The datasets used in the literature for the SP defects detection are mostly RGB. However, other researchers use solar thermal image datasets. In this research work, we use thermal images. This is because it was observed that the defects detection in RGB

such as cracks, diodes, junction are misclassified even with the functional SP as shown in Figure 9. The inference prediction on RGB looks indifferent from predicting the main defects or non-defects. Detection techniques like thermal imaging help make the defects part of SP more visible prior to the application of deep learning models as shown in Figure 10.

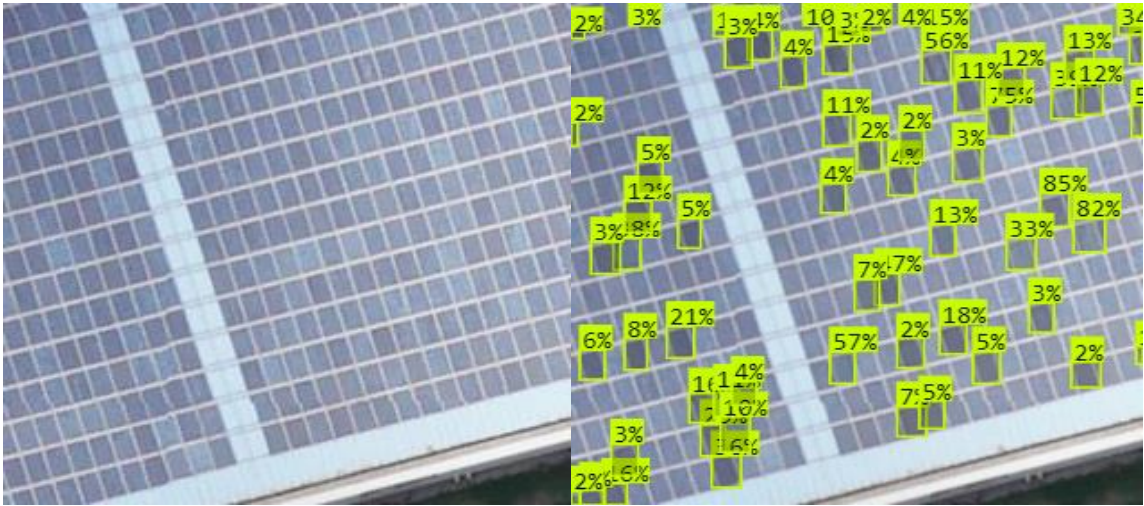


Figure 9: Defects detection on SP RGB with misclassification on both functional and defective SP

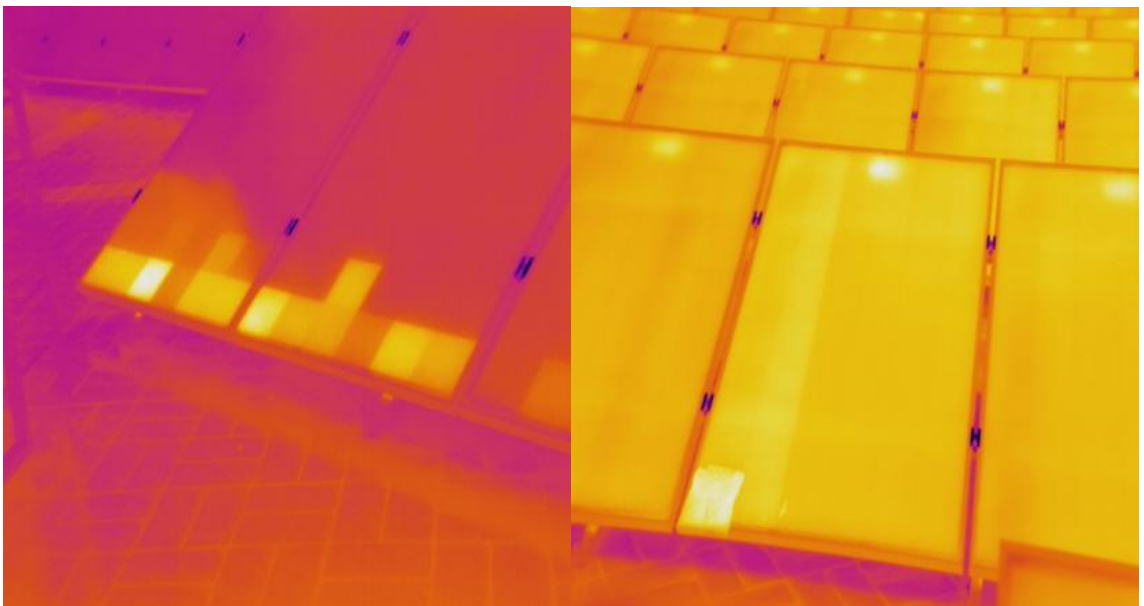


Figure 10: Visibility of defects after the application of Thermal Imaging detection techniques

So, the research work involves the use of a publicly available dataset with 1,036 high-resolution thermal images (captured using a thermal camera) of 640×640 pixels. Furthermore, the dataset was annotated in accordance with the COCO [58] object detection dataset format, encompassing the addition of bounding boxes and labels denoting defect classes. The process of annotation was facilitated using the Roboflow platform [59], a recognized tool for managing deep learning datasets. The dataset was collected from publicly available repository sources of Nanonets [60] and Roboflow [59]. Nanonets and Roboflow datasets have single defect class i.e., they both have annotation of just the defective spot on the SP images. Later through SDAIA, a set of 20 images from SAKAKA [61] solar plant having three defective classes, was included with the collected data.

Table 4 presents a comprehensive compilation of the dataset sources collected for this research study, along with the corresponding sample count for each source. The initial six datasets were excluded from the experiments conducted. This decision stems from the fact that these datasets consist of RGB images, and in some cases, the datasets lack annotated images. It is noteworthy that there are instances in the existing literature where RGB datasets were utilized for SP defect detection. However, the focus shifts to datasets comprising thermal images of SP, which prove to be instrumental in enhancing defect detection using deep learning models for object detection. As exemplified in Figure 11, a sample from this thermal image dataset and its background context were described. These two images highlight distinct aspects. The first image shows the SP along with potential defect region, while the second image emphasizes the broader context including the SP background.

Table 4: Summary of collected data for SP defects from publicly available sources.

No	Data Name	Authors	Type of Data Source	Number of classes		Data counts
1	Infrared SP Dataset	Matthew Millendorf, Edward Obropta, & Nikhil Vadhavkar	Research Paper published at ICLR 2020 in AI for Earth Sciences Workshop.	12 total classes	11 – Anomaly, 1 – No anomaly	20,000
2	Photovoltaic RGB image datasets	Vrai Team	Research team repository.	Anomaly and Non-Anomaly cells.		3,000
3	Crack Segmentation and Panel Images	Xin Chen <i>et al</i> , 2022	Research paper publish in ScienceDirect Solar Energy	Four Classes: Crack, Cross crack, Busbar and Dark area.		1,837
4	VisDrone2021, RGB, DET-test-challenge Dataset [47]	Zhu <i>et al</i> .	Research paper publish in IEEE/CVF	Satellite images with SP, pedestrian, cars, bicycle, and tricycle classes.		10,209
5	Satellite aerial RGB image, DuraMat DataHub [38]	Perry <i>et al</i> .	Research paper publish in IEEE Journal of Photovoltaics	Images with SP and non-solar panel.		860
6	Satellite RGB dataset of spatial resolutions of 0.1m, 0.3m and 0.8m. [42]	Jiang <i>et al</i> .	Dataset hub in Earth System Science Data	Classes are shrub land, grassland, cropland, saline-alkali, and water surface.		3,726
7	Nanonets solar thermal images [60]	Nanonets company	Websites	Single defect class		20
8	Roboflow Solar thermal Images [59]	Roboflow company	Dataset management websites	Single defect class		1,020

9	SAKAKA [61]	ACWA power company	Private experimental dataset	Three classes: Hotspot, Diode and Junction	16
					Total = 40,688

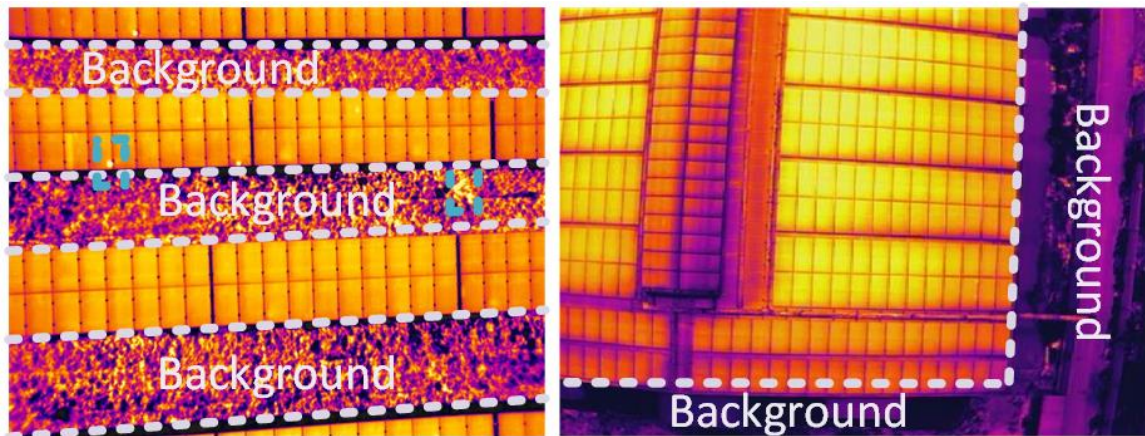


Figure 11: These images show typical examples of SP images captured using Thermal Imaging techniques.

The study undertakes a thorough analysis of deep learning models, notably the SegFormer segmentation model and initially, with experiments of YOLOv5 model on the three defects type of dataset. Then, six variants of YOLO object detection models were applied to a single defect type of dataset. By examining the difficulties associated with thermal image datasets, the study investigated techniques and approaches that can enhance the effectiveness of these models when applied to this type of dataset. Through rigorous experimentation and analysis, the research also reveals valuable insights into the refinement of model performance within the realm of thermal image-based PV system analysis.

3.2. Segmentation and Object Detection Architecture

Since commercial solar plants usually have millions of SPs to increase electricity generation capacity, replacing defectives SP is a more viable process. This is why studying defects detection in SPs becomes crucial. However, it is quite a challenge to detect defects accurately when the background blends with the defective SP, especially when a thermal imaging camera embedded with drones is used for capturing images of such PV plants. This was realized from the performance of application of YOLOv5 on the three defects type. To tackle this, we used a model called SegFormer [62], which is built on transformer technology, to segment the SPs from the background and compare the results with another techniques called K-means [63]. This step helps us focus better on detecting defects in SPs, making the approach more effective and accurate overall. Following the segmentation process, the next step involves identifying defects on the segmented SP. This is achieved by employing versions of YOLO object detection models on thermal image datasets of SP.

3.2.1. Segmentation models for SP Defects Detections

The challenge of capturing the SPs amidst the background using drones has led to the use of segmentation techniques to separate the SP from its environment. A K-means clustering model was first applied. Image segmentation using K-means typically involves partitioning an image into K clusters, where K is a user-defined parameter of real numbers. Since solar thermal image is a greyscale image [63], each pixel in the image is treated as a data point with a feature vector. The K-means model then groups these data points into K clusters in such a way that each pixel is assigned to the cluster whose center is closest to it in terms of some distance metric, typically Euclidean distance. In comparing the performances, a

specific type of segmentation model, called SegFormer [62], has been employed in this study. This model has demonstrated excellent performance on other various applications of image processing. SegFormer utilizes a Multi-layer Perceptron (MLP) decoder to gather information from different layers instead of relying on intricate decoders. The use of an MLP decoder in Segformer is crucial for addressing the unique challenges of the segmentation tasks. It helps in recovering spatial information, producing high-resolution output, refining feature representations, and integrating global and local context, leading to a better performance. An encoder captures essential features and patterns from the input data, while a decoder interprets the encoded information and generates the desired output.

To apply the SegFormer model for the segmentation of solar thermal images, the image dataset is first preprocessed and annotated manually one-by-one with the help of Roboflow [59] platform. The SegFormer model processes input images of size $H \times W \times 1$ (e.g., $640 \times 640 \times 1$) by breaking them down into smaller patches with each having size of $160 \times 160 \times 1$. These patches are then passed through a hierarchical transformer encoder to derive features at multiple levels, including $1/4$, $1/8$, $1/16$, and $1/32$ of the original image resolution (640). These resolutions correspond to sizes of 160, 80, 40, and 20, respectively, as illustrated in Figure 12.

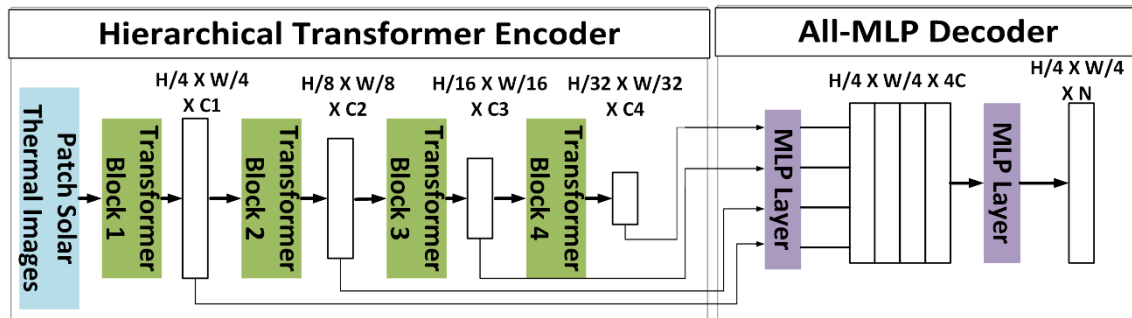


Figure 12: SegFormer segmentation techniques showing the hierarchical transformer encoder and All-MLP Decoder

These multi-level features are subsequently fed into an All-MLP decoder, which predicts the segmentation mask at a resolution of $H/4 \times W/4 \times N$. Here, N represents the number of classes of the defect. Each transformer block has N efficient self-attention and feedforward network blocks. Self-attention helps to capture the relations between input image patches, while the feed forward transforms the feature vectors into higher dimensional space and then back to its original dimension. Also, C1, C2, C3 and C4 are all 1.0 since thermal images are grey scale for one dimensional image.

To enhance performance, an ablation study was conducted to examine the impact of bilinear and bicubic interpolation techniques on the predicted segmentation mask. This primarily aimed to improve the quality of the predicted mask by the SegFormer model. The model generates masks through a specialized upsampling model followed by image filtering. This process, termed interpolation, creates a projected mask that is superimposed onto the original images. The study focused on evaluating the performance of two interpolation methods, namely, bilinear and bicubic. This is due to easiness in the implementation of both selected methods. Bilinear interpolation involves calculating a pixel's value by linearly interpolating the values of nearby pixels. On the other hand, bicubic interpolation employs polynomial interpolations of neighboring pixels to compute the value of a pixel. The segmentation method is followed by a detection approach.

3.2.2. Object detection models for SP defects detection

Following the implementation of the segmentation process, this research utilized variants of the YOLO (You Only Look Once) model to detect the locations of defects within the segmented thermal images. Six YOLO based models including: YOLOv5 [64], YOLOv5-

OBB [64], YOLOv6 [65], YOLOv7 [66], YOLOv8 [67] and YOLOS [68] were used for this purpose. The lower versions of YOLO variants (YOLOv1, YOLOv2, YOLOv3 and YOLOv4) were not used in this study because of their low performances on most benchmark datasets like COCO [58].

All YOLO variants take input images and divide each into a grid of cells. Each of these cells is responsible for detecting objects that are centered in the cell. The YOLO model can then predict the bounding box corresponding to each cell that has an object. A bounding box is defined by its center's coordinates (x, y) relative to the grid cell and its width and height (w, h) relative to the objects' dimensions. The center of the bounding box is usually represented by the midpoint of the box, while the width and height determine the size of the box.

In addition to predicting bounding boxes, YOLO assigns a class label with level of confidence to each detected object within a grid cell. To eliminate overlapping bounding boxes predictions, Non-Maximum Suppression (NMS) technique is applied to ensure that each object is detected only once. Also, for objects with diverse shapes and dimensions, anchor boxes are predefined. Each YOLO model also has a backbone network such as DarkNet, ResNet, Cross-Context Convolutional (C3), Vision Transformer, and Cross stage Partial Connection (CSP-Darknet). This helps to extract features from the input images. Hence, all YOLO models predict the bounding boxes with class labels.

The YOLO variants used in this study are as follows:

1. **YOLOv5:** is an upgraded version of the lower previous YOLO object detection models. Created by the Ultralytics [64] team, YOLOv5 aims to strike a balance

between accuracy and inference speed, making it useful for real-time applications. One standout feature of YOLOv5 is its simplified design, which reduces complexity while maintaining or even improving accuracy. YOLOv5 uses a CSP-Darknet53 backbone, which has special connections to help features flow better through different layers. Additionally, YOLOv5 introduces PANet (Path Aggregation Network) to gather information from different scales and depths, making detection even better.

2. **YOLOv5-ORB:** YOLO for Oriented Bounding Boxes [64] is a special upgrade of YOLOv5 model. It is developed for the purpose of finding objects with slanted boxes. It uses a Center-Scale-Line (CSL) label to represent the orientation of the bounding box. This is different from other YOLO models that use axis-aligned bounding boxes that are always horizontal or vertical. In a CSL labeled bounding box, the center of the box, the length of the box's diagonal, and the angle of the diagonal line are specified to accurately represent the object's orientation and location. On the other hand, an axis-aligned bounding box is a simpler way to define a rectangle around an object. In this case, the sides of the box are parallel to the image's horizontal and vertical axes.
3. **YOLOv6:** is a step forward to the previous YOLO object detection series [65]. It is designed to better spotting objects quickly and accurately in real-time scenarios. One key change is the new reparametrized backbone network known as EfficientRep and a Rep-PAN Neck to enhance its object detection capabilities. It also uses an anchor-free method unlike previous YOLO models. Traditional anchor-based models relied on predefined anchor boxes to detect objects at

different scales and aspect ratios, anchor-free models directly predict object bounding boxes without the need for anchors. These models have gained popularity in recent years due to their simplicity and effectiveness. In anchor-based object detection models (e.g., YOLOv5), a predefined set of anchor boxes is used to propose potential object locations. These anchor boxes are predefined in terms of sizes and aspect ratios and are used to regress and classify the objects within them.

4. **YOLOv7** [66]: is an improved version of the lower YOLO object detection models. It is designed to accurately spot objects in images or videos. YOLOv7 proposes backbone architecture called Efficient Layered Attention Network (E-ELAN), which helps collect various kinds of information from the image. Compared to earlier YOLO models, YOLOv7's use of E-ELAN allows it to be more accurate in detecting objects and understanding their context in the image.
5. **YOLOv8** [67]: is member of the series of YOLO models developed by Ultralytics just like the YOLOv5. It uses a modified version of CSP-Darknet53 as its backbones and integrates ability to customize anchor boxes unlike previous models with fixed predefined anchor-box sizes except YOLOv6 that uses anchor-free methods.
6. **YOLOS** [68]: is an object detection model that utilizes the vanilla vision transformer [69] as its backbone with a unique architecture called the Sequential Positional Encoding (SPE). Unlike previous YOLO models that are CNN-based, YOLOS includes a transformer-based block as its backbone. The YOLOS architecture comprises several layers of SPE blocks, followed by a transformer encoder block. The SPE blocks encode both spatial and sequential information of

image features, while the transformer encoder aids the model in learning contextual relationships between features.

During the process, a set of image patches and a set of detection tokens are inputted, as illustrated in Figure 13. MLP heads are then applied on top of these input sets. The detection token helps in recognizing objects and their positions within the input image through extracted features.

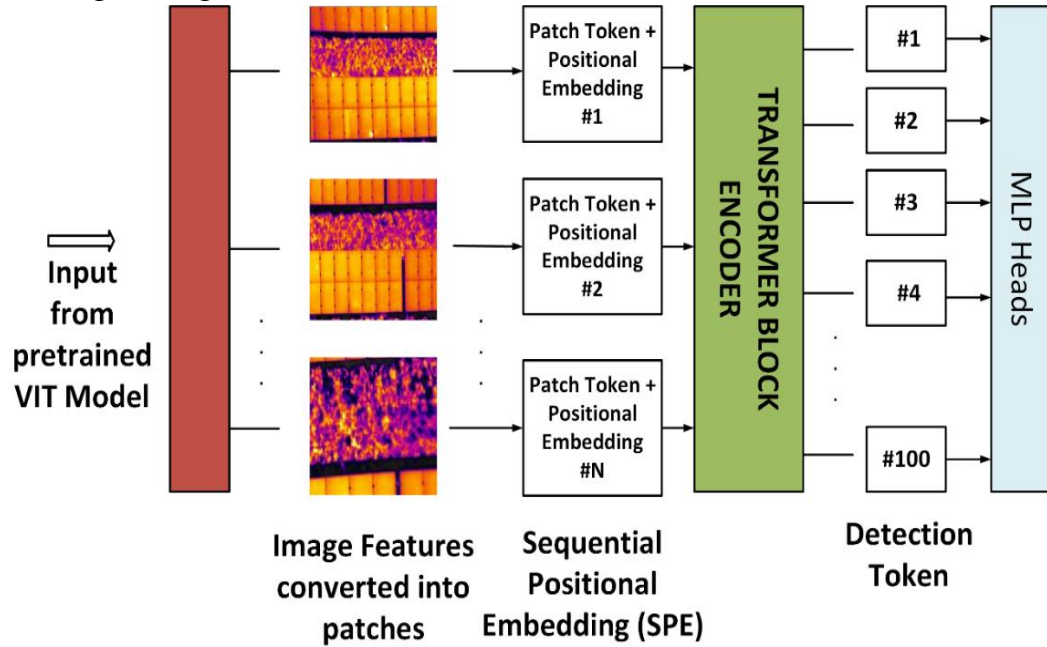


Figure 13: YOLOS model architecture on SP defect detection

Following the use of these object detection models on the segmented thermal image dataset, it was realized that the YOLOS model shows considerable promise in terms of its inference predictions, surpassing other YOLO models. Consequently, additional experiments were conducted to enhance and refine the YOLOS model's performance. Figure 14 shows a comprehensive overview of the process used in detecting SP defects — from the initial application of SegFormer Models to the subsequent employment of YOLOS models on the thermal SP dataset.

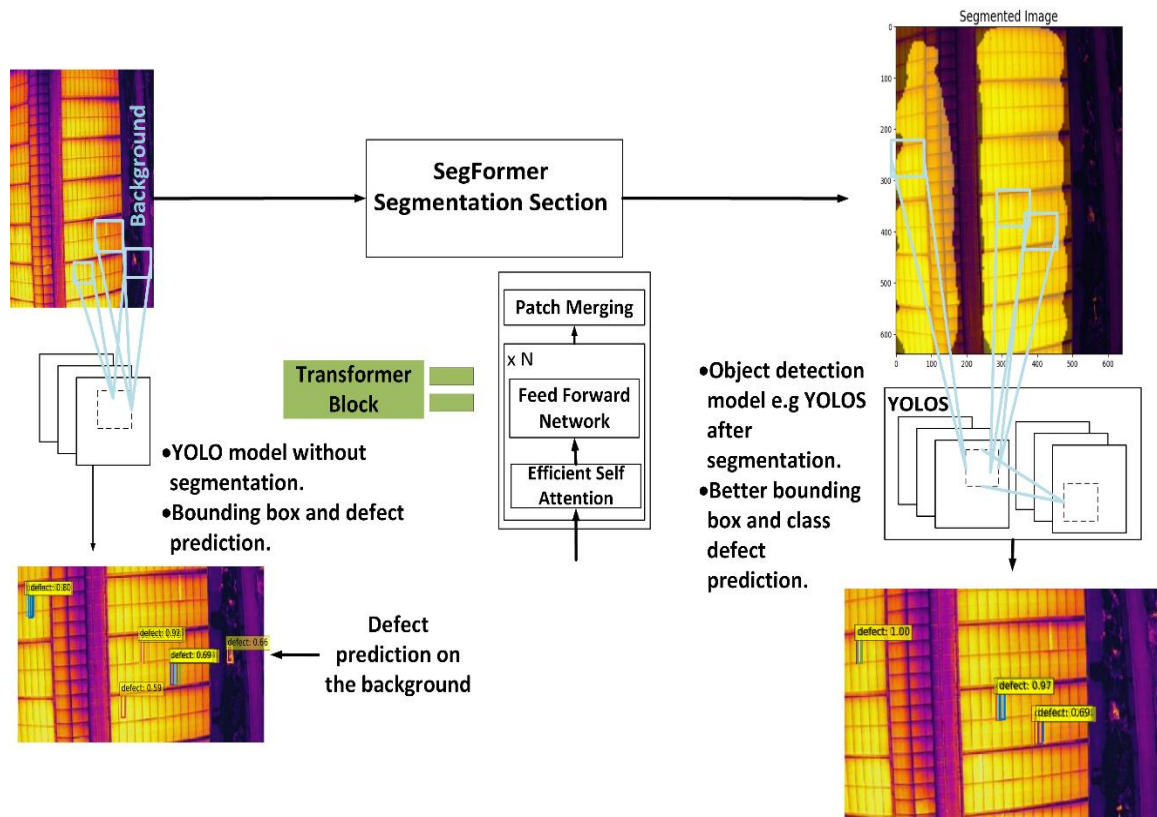


Figure 14: Flow diagram demonstrating the usage of object detection models (such as YOLO) on solar thermal images, with and without the use of segmentation techniques (SegFormer).

The flow diagram goes from the thermal images without segmentation as input to other YOLO variants models except YOLOS. This gives prediction of bounding boxes and class label on the background. However, when segmentation techniques are applied prior to YOLOS model, the predictions for bounding boxes and class labels are specific to the SP rather than the background. To further improve the performance, a YOLOS-PV model was developed in line with the YOLOS model as shown in Figure 15. The YOLOS-PV model introduces an adjustment to the bounding box loss employed in the YOLOS model.

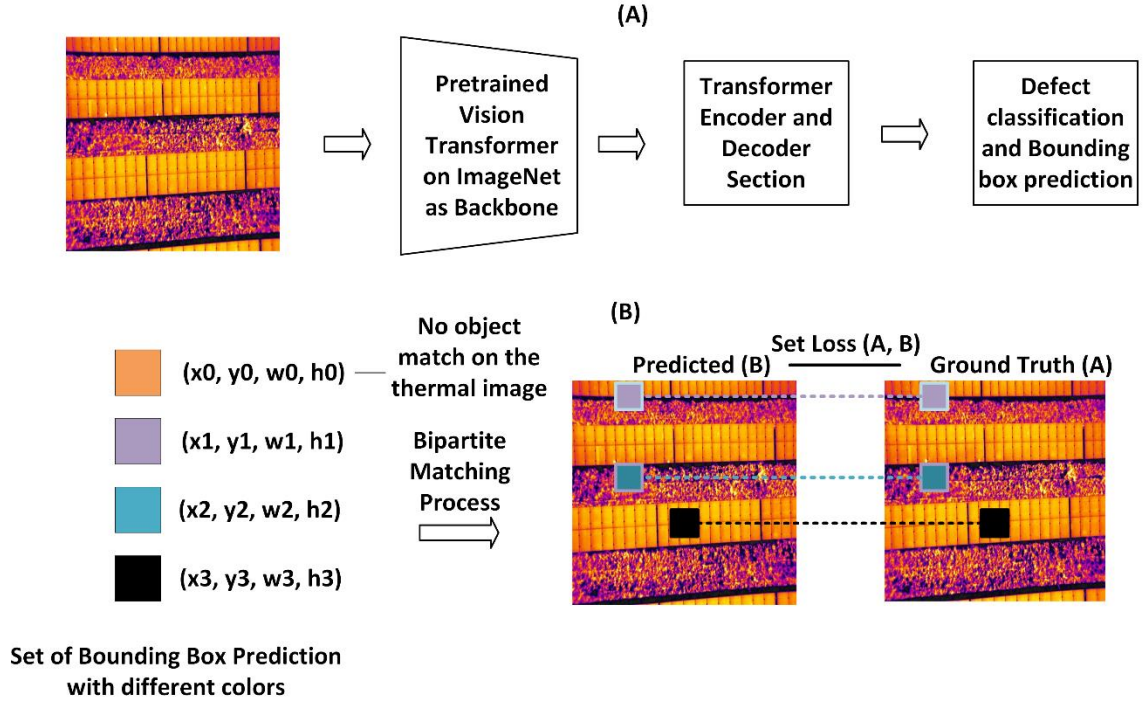


Figure 15: YOLOS-PV model's processing of solar thermal images by incorporating a pretrained Vision Transformer (ViT) as the backbone to extract features. The patch token and positional embedding are then passed through the transformer block encoder.

Since the YOLOS model does not include NMS process, the predicted bounding box sometimes overlapped. Hence, instead of a linear combination of the loss function, a weighted loss approach was used. While the YOLO models typically share a similar loss function, YOLOS uses different loss function by adopting similar one to that of DETR [52], an End-to-End Object Detection model renowned for its incorporation of transformers. The DETR model employs a unique set of loss functions that treats object detection as a set prediction task, unlike traditional methods that rely on region proposals. The loss function contains two terms - the Binary Cross-Entropy (BCE) Loss, which measures the loss for object predictions (finding out if an object exists in a particular class), and the Set Loss, which calculates the bipartite matching between predicted and actual object sets.

$$\text{BCE Loss: } BCELoss(y, \hat{y}) = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (7)$$

$$\text{Set Loss: } SetLoss(A, B) = BCELoss(C(A), \hat{C}(B)) + \lambda \cdot L_{\text{box}}(b_i, \widehat{b}_\sigma(i)) \quad (8)$$

$$\text{Where } L_{\text{box}}(b_i, \widehat{b}_\sigma(i)) = \lambda_{giou} GIoU_{iou}(b_i, \widehat{b}_\sigma(i)) + \lambda_{L1} \|b_i - \widehat{b}_\sigma(i)\|_1$$

and y represents the ground truth binary labels (0 or 1) for the N samples, $\hat{y}$ represents the predicted probabilities for the positive class, A is the ground-truth object set, B is the predicted object set, $C(A)$ is the binary mask indicating presence or absence of objects, $\hat{C}(B)$ is the predicted mask, b_i is the ground-truth bounding box location matrix, $\widehat{b}_\sigma(i)$ is the predicted matrix, and λ is a balancing hyperparameter. $\lambda_{giou} = 5$, $\lambda_{L1} = 1 \in R$, $GIoU_{iou}$ is the generalized intersection over union (GIoU) between b_i and predicted bounding box $\widehat{b}_\sigma(i)$, and $\|\cdot\|_1$ denotes the L_1 norm. The losses are normalized by the number of objects in the batch. The GIoU loss is a metric used to quantify the dissimilarity between two bounding boxes. It considers not only the overlap between the two boxes but also their structural differences. The GIoU is given as follows:

$$IoU(B_{\text{pred}}, B_{\text{gt}}) = \frac{\text{area}(B_{\text{pred}} \cap B_{\text{gt}})}{\text{area}(B_{\text{pred}}) + \text{area}(B_{\text{gt}}) - \text{area}(B_{\text{pred}} \cap B_{\text{gt}})} \quad (9)$$

$$\begin{aligned} GIoU(B_{\text{pred}}, B_{\text{gt}}) &= IoU(B_{\text{pred}}, B_{\text{gt}}) \\ &\quad - \frac{\text{area}(\text{enclosing box}(B_{\text{pred}}, B_{\text{gt}})) - \text{area}(B_{\text{pred}} \cap B_{\text{gt}})}{\text{area}(\text{enclosing box}(B_{\text{pred}}, B_{\text{gt}}))} \end{aligned} \quad (10)$$

where B_{pred} is the predicted bounding box, B_{gt} is the ground truth bounding box, and

enclosing box (B_{pred}, B_{gt}) is the smallest bounding box enclosing both B_{pred} and B_{gt} .

L_{box} is a linear combination of GIoU and L1 regression loss in equation (8). The L1 loss for a single object i is defined as the sum of the absolute differences between the predicted and ground-truth bounding box coordinates and sizes:

$$L1\ loss_i = |x_i - x_{i0}| + |y_i - y_{i0}| + |w_i - w_{i0}| + |h_i - h_{i0}| \quad (11)$$

The predicted bounding box coordinates and sizes for each of these objects are denoted as (x_i, y_i, w_i, h_i) , where i ranges from 1 to N . Similarly, the ground-truth bounding box coordinates and sizes are denoted as $(x_{i0}, y_{i0}, w_{i0}, h_{i0})$. The linear combination of GIoU and L1 losses in equation (8) is suboptimal for certain types of problems. This is used to address the issue of different scales for small and large boxes, even with similar relative errors as proposed by [52]. However, when applied to defect detection in SP using YOLO models, the use of a linear combination of losses leads to suboptimal predictions of bounding boxes for defects during inference. This often results in overlapping bounding boxes for different object classes. Applying a weighted loss combination resolves this issue by assigning higher priority to either GIoU or L1 loss, effectively suppressing unwanted bounding box losses. This is one of the contributions of this study.

Hence,

$$\begin{aligned} & Weighted_{L_{box}}(b_i, \widehat{b}_\sigma(i)) \\ &= \frac{\left(W_{giou} \times \lambda_{giou} GIoU_{iou}(b_i, \widehat{b}_\sigma(i))\right) + \left(W_{L1} \times \lambda_{L1} \left\|b_i - \widehat{b}_\sigma(i)\right\|_1\right)}{W_{giou} + W_{L1}} \quad (12) \end{aligned}$$

where W_{L1} is the hyperparameter weight assign to L1 regression loss and W_{giou} is

the weighted value assign to the GIoU loss. The $W_{L1} + W_{giou}$ value is always 1.

3.3. Training Techniques for Segmentation and Detection Models

The research work was conducted using the Google Colab platform, which offers access to both CPU and GPU resources, with notable GPUs such as NVIDIA Tesla K80, T4, P4, and P100 GPUs. These GPUs play a crucial role in accelerating deep learning tasks, resulting in faster training durations. Additionally, Google Colab grants storage accessibility via Google Drive, facilitating easy dataset access for training purposes. This is utilized in this study for the SP detection training process.

The training process for the six YOLO variants, including the suggested YOLOS-PV, was conducted over the course of 100 epochs. A batch size of 16, an image resolution of 640, a learning rate of $2.5e-5$, and a weight decay of $1e-4$ were applied consistently across these models. These parameters were selected based on initial experimentations.

3.4. Performance Evaluation of the selected models on SP Defects Detection

The results are categorized into two distinct sections: segmentation and detection. Segmentation encompasses the results derived from the SegFormer model, while the detection results pertain to the detection of defects within solar thermal images, obtained using various YOLO model variants.

3.4.1. Performance of Segmentation

The strategy involved the implementation of segmentation models to differentiate the background from the SP in the solar thermal images obtained from the drones. Firstly, K-means clustering model was applied to the solar thermal images with variation of hyperparameter K of 1,2,3,4 and 5. At $K = 5$ upward, the image results look similar. The result is shown in Figure 16 with the defects in some solar thermal images completely blend with the environment. This shows that the use of simple techniques like K-means cannot be applied for the segmentation purpose. Consequently, the SegFormer segmentation model was employed, resulting in a mean intersection over union (mIoU) score of 86.1% and a 92.4% (mAcc). The outcome in Figure 17 demonstrates the model's effective segmentation of SP within solar plants with the defects not blending with the environments; however, there is room for enhancement in performance. This is evident from the test, segmented, and ground truth images, where the segmented images do not precisely match the ground truth.

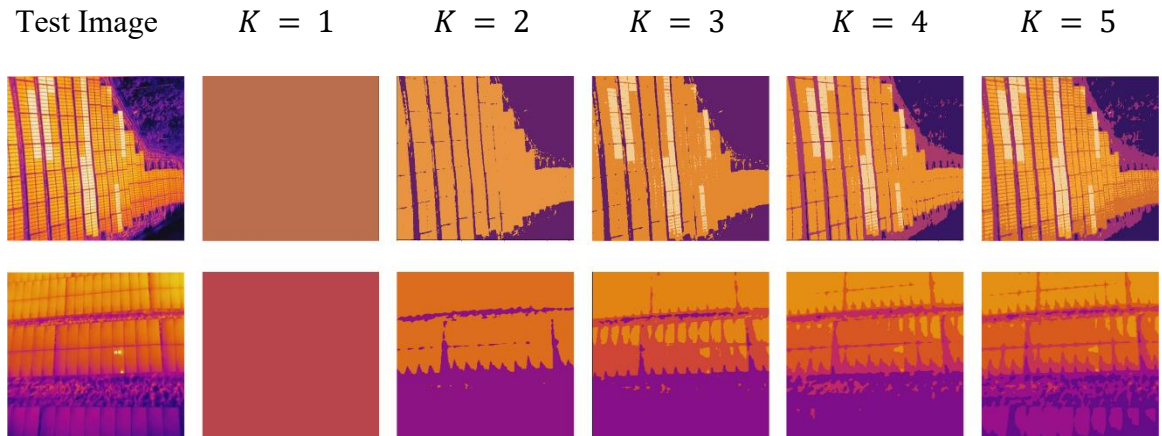


Figure 16: K-means results on test solar thermal images with $K=1,2,3,4,5$

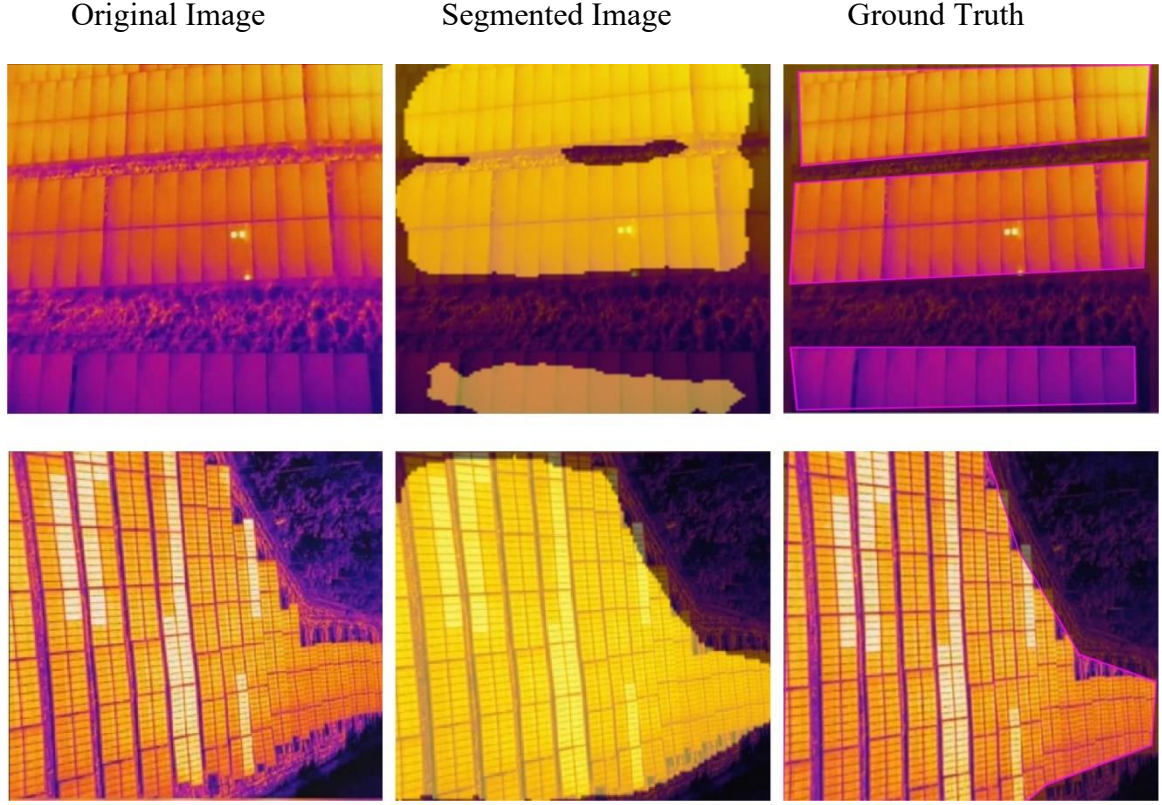


Figure 17: SegFormer segmentation model results on test solar thermal images. The results show the segmented, ground truth and the test thermal images.

To enhance the segmented area produced by the SegFormer models, an ablation study was conducted. This study involves the application of distinct upsampling techniques, namely bilinear and bicubic, to the experimental segmentation results for generating segmented masks. The findings indicated that bicubic interpolation gave better performance, as depicted in Figure 18 based on the mask coverage criteria. Notably, while bilinear interpolation has reduced noise, it covered a smaller region within the mask when compared to bicubic interpolation.

When compared to other segmentation models such as U-Net, RefineNet, and DeepLabv3+ that have been employed for SP segmentation, the SegFormer model demonstrates a better mean intersection over union (mIoU) value of 86.1%, as depicted in Table 5.

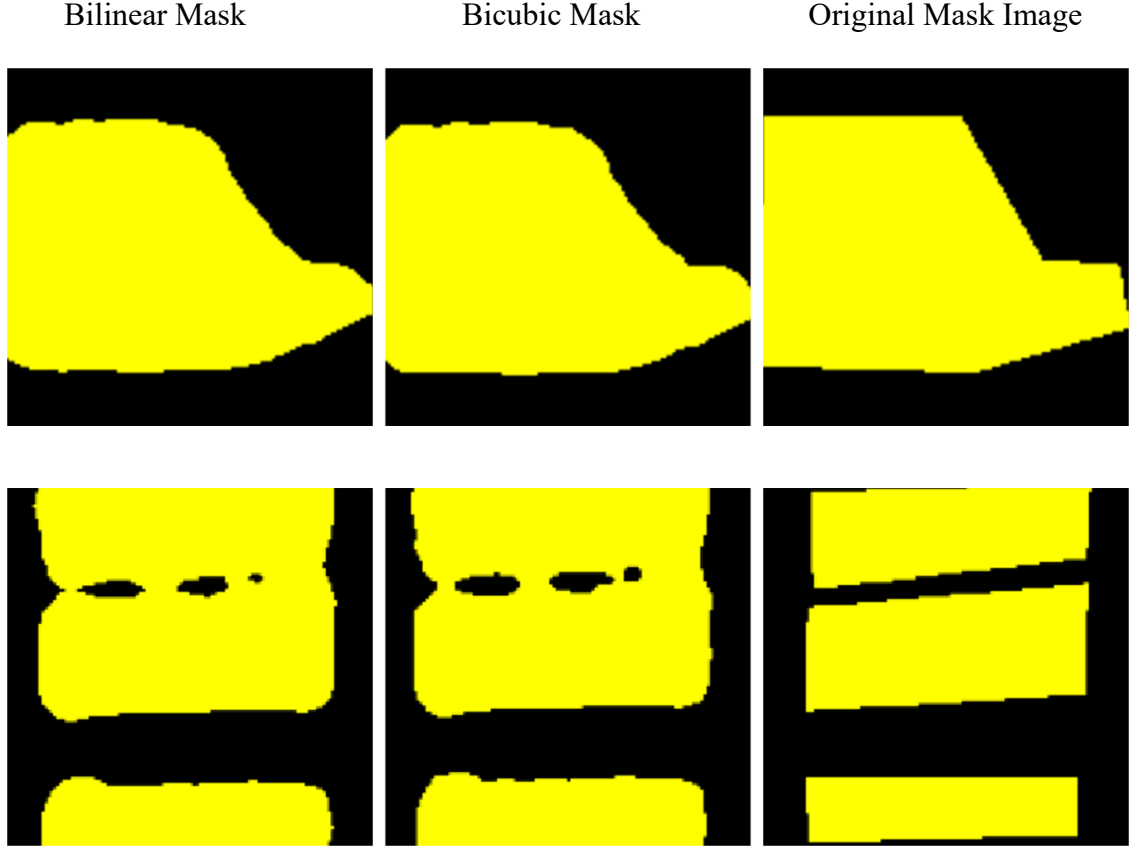


Figure 18: Ablation studies in segmentation model using Bilinear and Bicubic.

While most of the similar work in the literature did not use mean accuracy, the SegFormer model on SP thermal images gave 92.4% mAcc. In summary, the study applied segmentation models to distinguish SP from the background in solar thermal images. The SegFormer segmentation model achieved a mIoU score of 86.1% and a mean accuracy of 92.4%.

Table 5: Mean IoU and mean accuracy results of segmentation models comparison

Models	Data Type	mIoU (%)	mAcc (%)
SegFormer*	Thermal Images	86.1*	92.4
EfficientNet-B7 based U-Net (31)	RGB Images	86.0	-
ResNet-34 based U-Net (35)	RGB Images	84.0	-

U-Net, RefineNet, DeepLabv3+ (36)	RGB Images	85.0	-
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To refine segmentation, an ablation study was applied using different upsampling methods—bilinear and bicubic. Bicubic interpolation outperformed bilinear interpolation, exhibiting better mask coverage.

3.4.2. Performance of Detection

The SegFormer model's output was then utilized by applying object detection models, namely YOLO models, to detect the defects. The experiments conducted were, firstly, on three classes of defects called hotspot, diode, and junction defects using YOLOv5 specifically. A hotspot is a defect that occurs because of extreme heat above $1,000 \text{ W/m}^2$ on the SP. Diode defects occur because of the installation issue in the bypass diode component. The bypass diode components helped ensure no reverse current pass through to the SP from the storage at night. Similarly, junction box effects occur because of defects in the junction box components. The junction box components helped ensure the connected wires are protected and centralized.

Then, the second experiment focused on the defective and non-defective class. This is due to the unclear identification of the type of defects on the solar plant. When the drone captures thermal images depending on the drone's height, all three defects appear the same. This raises the challenge of distinguishing between hotspot, diode, or junction defects. This presents a major challenge in using deep learning models to classify such defects. Even though the performance of the three defects was not convincing as shown in Figure 20, the single defect experiment was conducted because of the unclear identification of the three

types of defects on the SP. Hence, further experiments were conducted using six YOLO variants, namely YOLOv5, YOLOv5-OBb, YOLOv6, YOLOv7, YOLOv8, and YOLOS, on the defective and non-defective class.

The transformer based YOLOS model had the best $mAP@0.5:0.95$ value of 86.7% and $mAR@0.5:0.95$ value of 95.2%. The $mAP@0.5$ metric measures the average precision when the IoU threshold is set to 0.50, and $mAP@0.5:0.95$ measures the average precision when the IoU threshold is varied from 0.50 to 0.95 with a step of 0.05. The range specifies that the AP is calculated at ten different IoU thresholds, ranging from 0.50 to 0.95. A $mAP@0.5$ of 1.0 or 100% indicates perfect performance, while a value of 0.0 or 0.0% means that the model failed to detect any defects. Each model was evaluated on a test dataset as shown in Figure 20. It was realized that the YOLOS model has better inference performance having highest number class labels confidence of 1.0 in all inferences, but with overlapping bounding box prediction in some cases. The bounding box distortion was addressed with the help of bounding box loss function adjustment by introducing two weight hyperparameters, W_{L1} and W_{giou} .

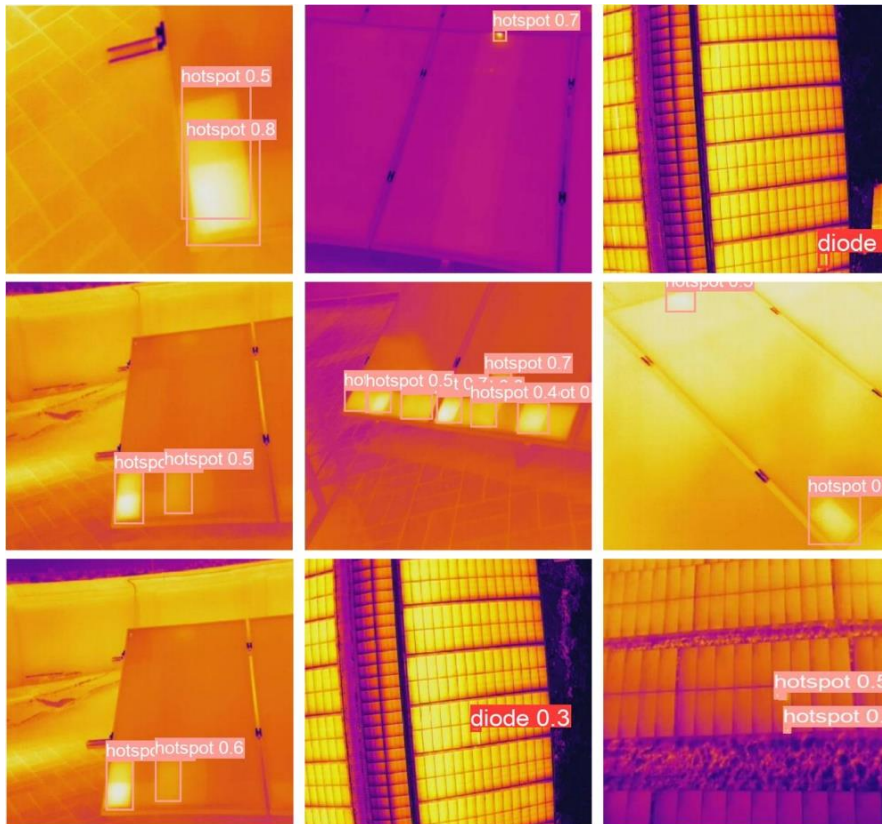
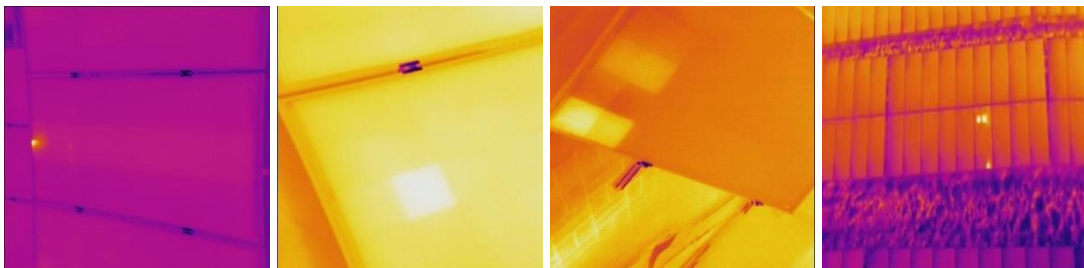
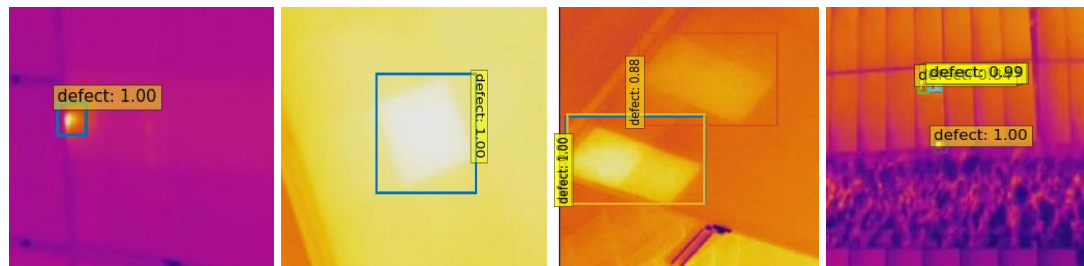


Figure 19: Results of YOLOv5 low performances on test dataset for hotspots, diode, and junction classes

Test Images



YOLOS



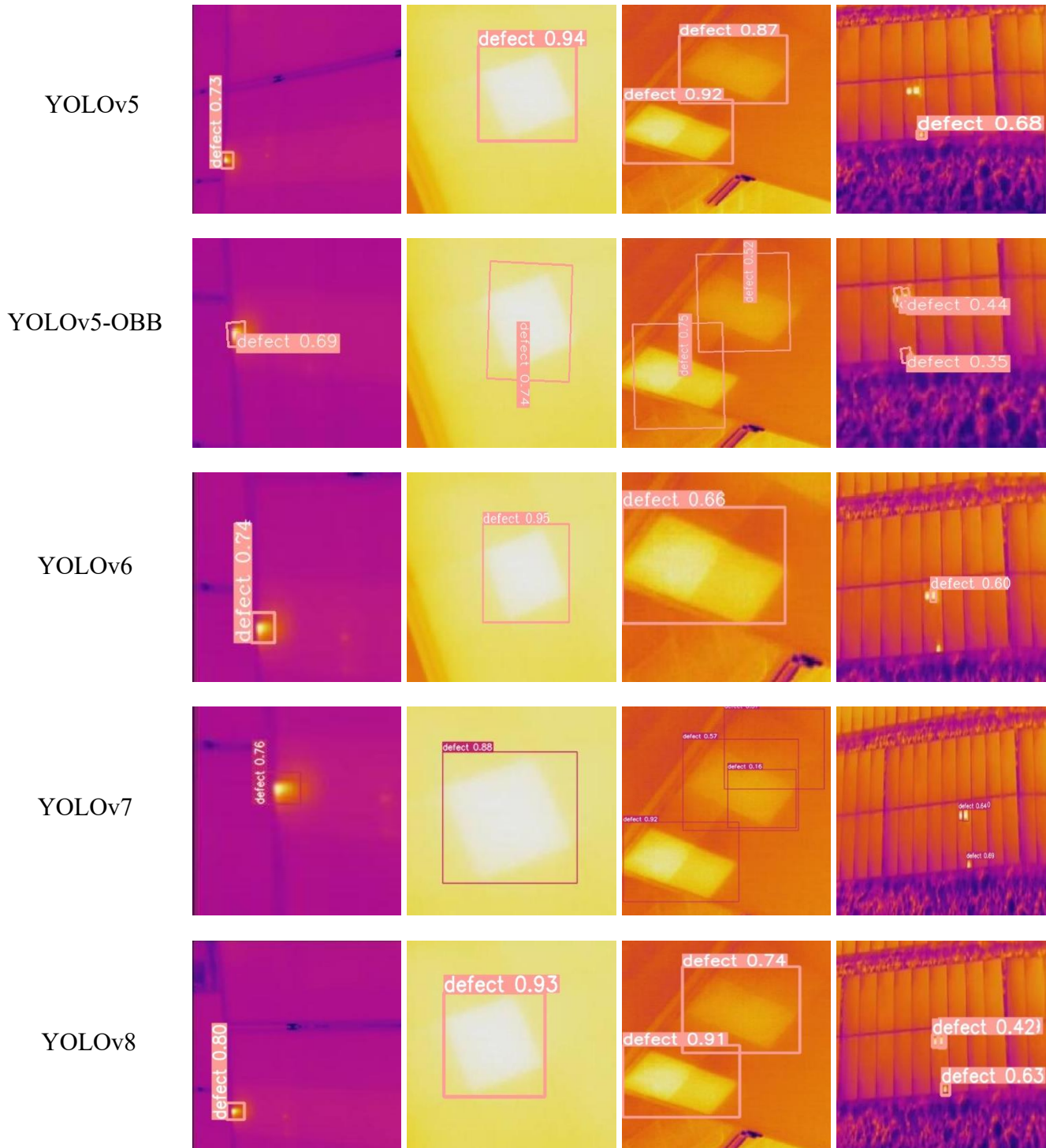
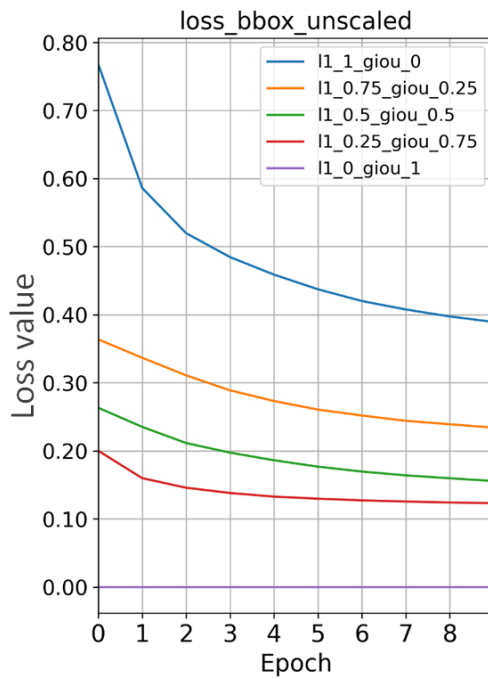
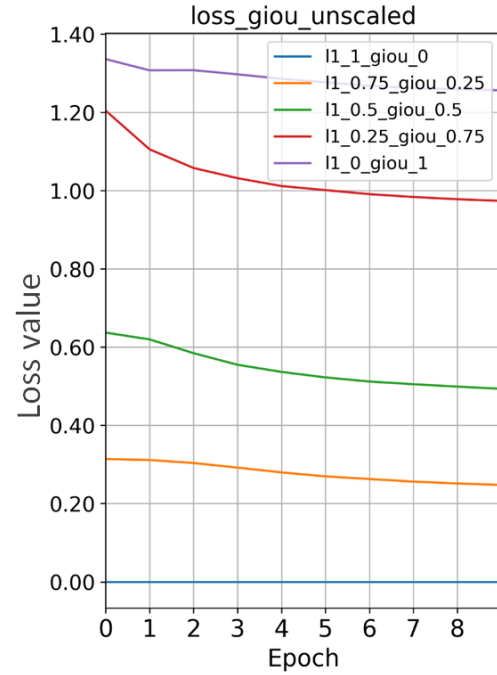


Figure 20: Inference experimental results on solar thermal images using six YOLO variants for a defective class. To evaluate the weight hyperparameters impact, the values were varied independently from 0.0 to 1.0 in an increment of 0.25, with the two weights always summing up to 1.0. The

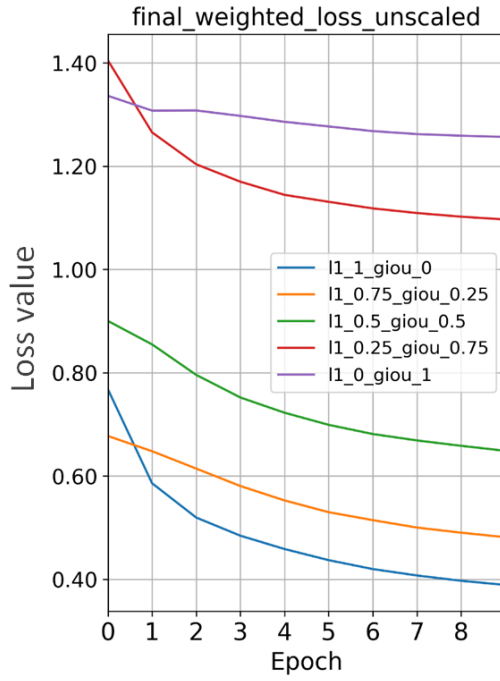
evaluation was conducted within a window of 10 epochs, specifically from epoch 50 to epoch 59 as shown in Figure 21. Based on [70], it was concluded that the weighted combination of $W_{L1} = 0.250$ and $W_{giou} = 0.750$ proved to be the most effective, as shown in Figure 22 since it gives a recommended good learning rate. This determines the rate at which network's weights are updated during training. High learning rate caused model to converge quickly but overshoot the optimal network's weights. While low learning rate caused the model to get stuck in a suboptimal solution. The two selected weights yielded a more favorable learning rate compared to other combinations with either higher or lower weights. Correspondingly, the outcomes of both the YOLOS and YOLOS-PV models, based on the bounding box predictions output on the same inference thermal images, are presented in Figure 23.



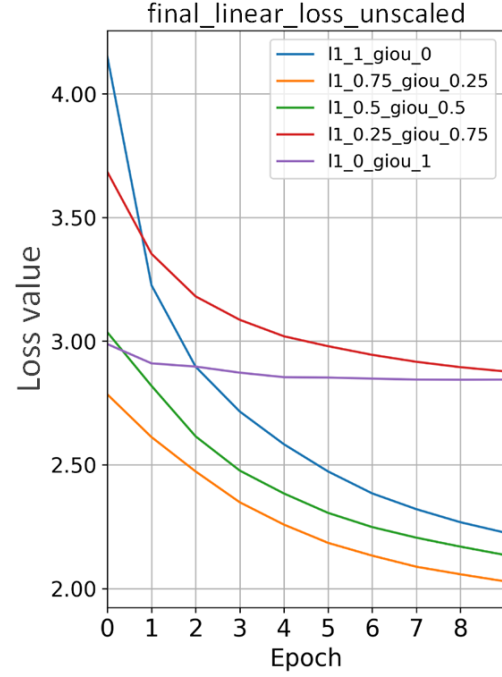
(a)



(b)



(c)



(d)

Figure 21: (a) L1 loss (b) GIoU loss (c) Final weighted loss (d) Final linear combination loss. The weight hyperparameters are W_{L1} (l1) and W_{giou} (giou) for the defect's detection in solar thermal images. A weight of l1 = 0.250 and giou = 0.750 gives a better weighted loss combination.

Loss vs Epochs showing different Learning rate

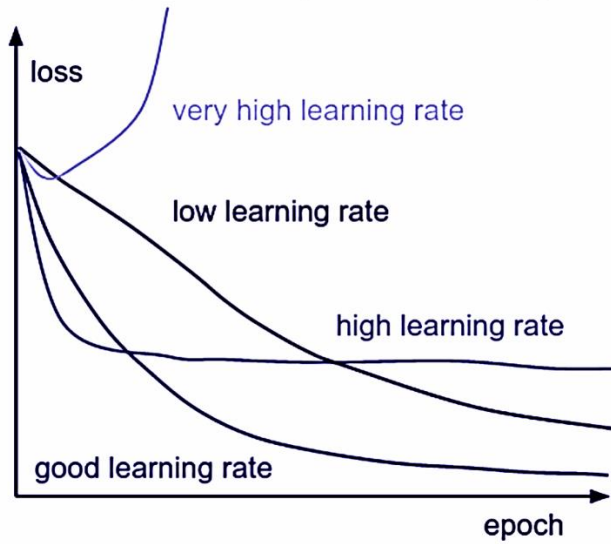


Figure 22: Loss vs Epoch plots showing different learning rate [70]

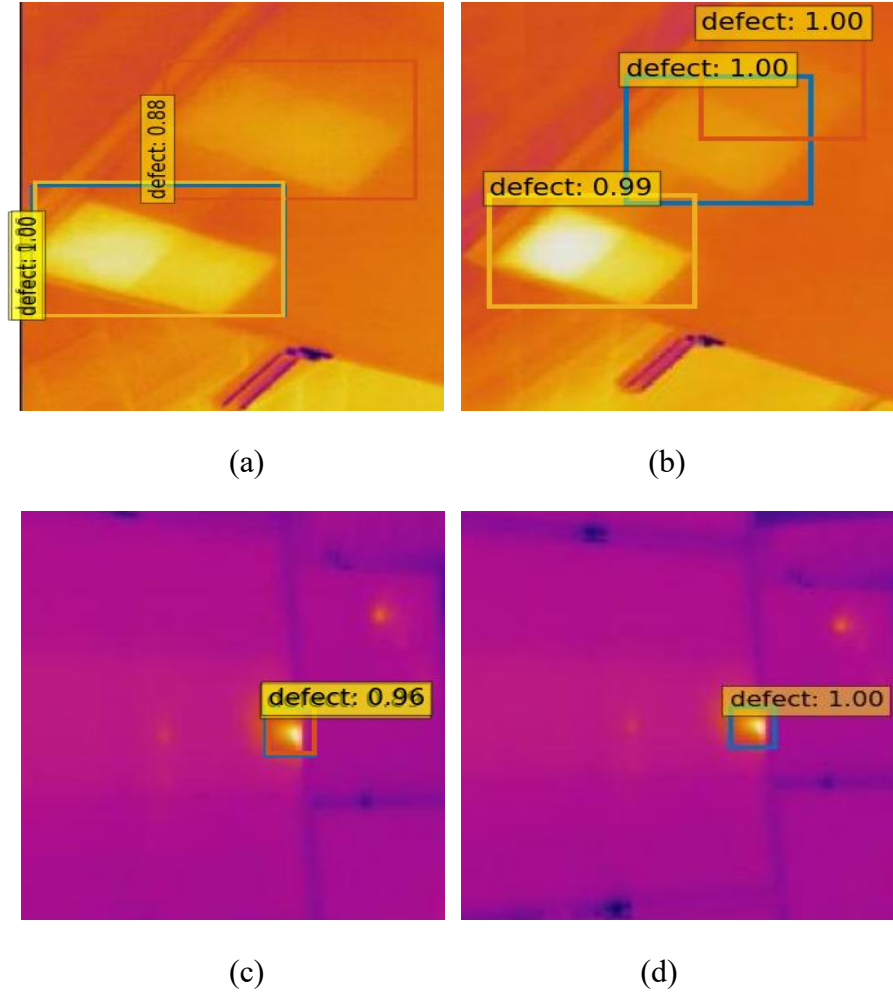


Figure 23: Results comparison of (a) and (c) for YOLOS Model (Linear bounding box loss function) and, (b) and (d) for YOLOS-PV Model (Weighted bounding box loss function)

This shows that YOLOS-PV has better bounding box selection without overlapping each other. Table 6 shows the comparison of developed YOLOS-PV model result with the other six YOLO models' variants including results from the literature. This shows that the developed model has a better performance with $mAP@0.5:0.95$ of 89.4% and $mAR@0.5:0.95$ of 95.2%. The mAR for both YOLOS and YOLOS-PV are the same indicating that both models can correctly identify defects instances on average with the same performance given the same inference dataset across different classes. However,

YOLOS-PV has better inference bounding box selections by removing the overlapping boxes.

Table 6: Object detection YOLO variants model results on solar thermal images

Models	mAR @0.5:0.95 (%)	mAP @0.5:0.95 (%)
Zhu et al. (TPH-YOLOv5) (42)	-	39.4
Pathak et al. (faster RCNN) (44)	-	67.0
Sun et al. (YOLOv5) (45)	-	87.8
YOLOv5	-	25.8
YOLOv5-OBB	-	15.3
YOLOv6	-	76.7
YOLOv7	-	37.0
YOLOv8	-	46.3
YOLOS	95.2*	86.7
YOLOS-PV (Ours)*	95.2*	89.4*

In summary, the use of a weighted bounding box loss function, as detailed in YOLOS-PV has $\text{mAP}@0.5:0.95$ of 89.4% and provides more favorable inference outcomes compared to the YOLOS model with $\text{mAP}@0.5:0.95$ of 86.7%. The absence of NMS techniques in the YOLOS model often resulted in overlapping bounding boxes during inference predictions. Employing a weighted loss function was a strategic solution to mitigate these challenges, particularly when it came to detecting defects in SPs. The results presented a notable enhancement in separating overlapped bounding boxes along with improved confidence class labels.

CHAPTER 4

SOLAR CELLS DEFECTS CLASSIFICATION

The research work continues with the SC defects classification. SC defects can manifest as structural damage, material impurities, or functional abnormalities that compromise the cell's ability to convert sunlight into electrical energy. Analyses were performed on SC defects because of the constraint of some certain defects like microcracks, snail trails and picker print that cannot be easily seen with naked eyes both on RGB and thermal images from the drone. However, these defects can be seen with the help of Electroluminescence (EL) phenomenon on the SC [34]. The EL process is usually in the laboratories, and it is mostly conducted in dark rooms for better visibility of the defects. This is why the drones cannot be effectively used for detecting defects in SC. In this study, the EL process was not conducted, but the available dataset in the literature was utilized to perform the classification analyses. Subsequently, suitable deep learning models were selected and trained on the SC datasets. These models' performances were assessed employing common evaluation metrics for classification tasks, including precision, recall, F1 score, and accuracy.

4.1. Dataset Collection and Preprocessing for SC

After a thorough search for SC defect datasets that are collected from the output of the EL techniques, the dataset collected from various sources are given in Table 8 with total number of samples of 87,789. Among these, the elpv dataset is used in this study for SC

defect classification and the results collected were compared with the existing results in the literature. This dataset is termed elpv-4 as Electroluminescence Photovoltaic dataset with four classes (functional, moderate, mild, and severe). The description of each class dataset is given below:

1. Functional: This is the non-defective SC in the dataset. The dataset is labelled in probability of defective. For instance, in this case, a single cell categorized as functional in the dataset means that the defective probability value is 0.0 while functional probability value is 1.0.
2. Moderate defect: A cell categorized as moderate defect means that the defective probability value is 0.33 and the functional probability value is 0.67.
3. Mild defect: A mild defect cell means that the defective probability value is 0.67 and the functional probability value is 0.33.
4. Severe defect: A severe defect cell means that the defective probability value is 1 while the functional probability value is 0.0.

Two of the four classes were combined to form single class and the other two to form another class. The functional and moderate classes are categorized as functional while mild and severe were combined as defective to be suitable for binary classification problems. The resulted two classes are referred to as elpv-2. This method is proposed in the literature to reduce the number of classes of elpv-4 to two [35]. By doing this, the performance accuracy score improved due to less variants of the dataset with two classes. To further improve the reliability of the developed models, a large amount of dataset is also needed for training deep learning models [71]. Hence, a dataset of 11 defects classes in addition to the functional SC were collected from different sources from the literature. The sources

include: 2,624 of elpv-4, 1,031 samples classified as cracks, corroded, and good, 36,543 samples of Photovoltaic EL Anomaly Detection (PVEL-AD) images, and a final dataset containing 1,837 images that are classified as crack, cross-crack, busbar, and dark area. These collected datasets were used and termed as elpv-12 as shown in Figure 5. Table 7 shows a summary of these three elpv datasets: elpv-4, elpv-2 and elpv-12 utilized in this research work.

Table 7: Summary of the elpv dataset with collection of elpv-2 and elpv-12

Dataset	Total Data	Classifications
elpv-2 (collected)	2,624	functional and severe
elpv-4	2,624	functional, moderate, mild, and severe
elpv-12 (collected)	18,347	Back contacts (72), Cracked (878), Edge Isolation (303), Fingerprint (119), Hotspot (210), Picker Print (81), Corroded (191), Dark area (1,149), Edge shunt (20), Good (1,044), Multi defects (59) and Soiling (14,221).

The elpv-2 and elpv-4 datasets each have a training set of size 1,890 and a test set of 734. Both datasets include 2,624 total samples with 300×300 pixels, and 8-bit grayscale images from either monocrystalline or polycrystalline SP. The elpv-12 comprises of a total of 18,347 samples retrieved from publicly available elpv datasets. Most of the datasets used in elpv-12 are collected from PVEL-AD which has eight classification categories. However, the elpv-12 dataset is skewed towards SCs such as cracked, dark area, good and soiling. As a result, there is an imbalance in the class.

Table 8: Summary of collected data for SC defects from publicly available sources.

No	Data Name	Authors	Type of Data Source	Number of classes		Data counts
1	Electroluminescence images (300×300 Defective cell) (Benchmark) [35]	Buerhop-Lutz, C, Deitsch, S	Research Paper published in <i>PeerJ Computer Science</i> .	4 classes	Not defected, possibly normal, possibly defected, defected	2,624
2	Soiling defect RGB images	Sachin Mehta	Research paper published in <i>Applied Energy</i>	Power loss, Solar irradiation, and timestamp labels		45,754
3	Electroluminescence images (Cracks and Corrosion)	Roger H. French	Research Paper publish in <i>IEEE Journal of Photovoltaics</i> .	3 Classifications: Cracks, corroded and good.		1031
4	Photovoltaic Cell Anomaly Detection Dataset (infra-red images)	Binyi Su	Research paper publish in <i>IEEE Trans. Ind. Inform</i>	12 classes with 8 kinds of defects.		36,543
5	Crack Segmentation	Xin Chen <i>et all</i> , 2022	Research paper publish in <i>ScienceDirect Solar Energy</i>	Four Classes: Crack, Cross crack, Busbar and Dark area.		1,837
Total = 87,789						

The data imbalance was addressed by increasing the lowest number of classes while reducing the highest number of classes (e.g., soiling). The data was increased through data

augmentation techniques that transform the original image using various methods of scaling, horizontal and vertical flipping, cropping and rotation. While similar variants of the soiling defects were removed to give the same sample of dataset.

From the available image transformation techniques, the vertical and horizontal flipping of the images were selected, along with the addition of random brightness and contrast within the respective ranges of 0.65 to 1.35 and 0.5 to 1.5. The choice of these specific techniques is because the elpv-12 dataset contains gray-scale images. More advanced techniques such as cropping, color augmentation, rotation, and the addition of noise to the image are unlikely to improve the context of the data and may not be encountered in the real data. Therefore, only the selected image transformation techniques were used to augment the data. The link of the collected elpv-12 dataset can be found in [72].

4.2. Classification Models for SC Defects

For the SC defect problems, a set of image classification models were selected based on their widespread use and proven success. The chosen models include well-known architectures like AlexNet, GoogleNet, ResNet, and SENet, and all of which have been successful in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) on various occasions - specifically in 2012, 2014, 2015, and 2017, respectively [71]. These models are commonly employed in image recognition tasks, and their collective record made them natural choices for this problem. SP defect problems have been addressed using some of the deep learning models selected like AlexNet and ResNet but still need more exploration for other models as new models have frequently been built overtime. In this study, experiments were conducted using twelve models with a record of strong

performance on image classification problems. These models include AlexNet, ResNet18, ResNet34, ResNet50, ResNet101, ResNet152, SENet, GoogleNet, Xception, Vision Transformer (Vit), YOLOv3, and SqueezeNet. The models were applied to three set of elpv datasets using different hyperparameters for each set, with the aim of classifying defects in SC. These experiments help in evaluating the performance of each model. The description of the models is given as follows:

1. **AlexNet:** is a sequential model with eight layers consisting of five convolutional layers followed by maxpooling and the last three are fully connected layers. It has 60 million parameters and 650,000 neurons [73]. The architecture was developed to support training on Multiple GPUs that reduces training time due to limited memory of 3GB for early GPUs. They have been increased up to 80GB [74] nowadays.
2. **SENet:** uses the concept of Squeeze-and-Excitation (SE) block that helps to model the interdependencies between channel of images so that it can be sensitive to features [75]. The squeeze operation or global information embedding involves converting feature maps (resulting image after the convolution of filter matrix with input image matrix) into a single value for each channel using global average pooling. The excitation operation or adaptive recalibration is then used to convert the single value to a channel weight of the same size as the input. The SE blocks are stacked with other architectures like ResNet and Inception that utilize residual and inception module, respectively. In this work, the SE blocks were stacked with the residual module.

3. **GoogleNet:** involves applying the concept of inception module in the network. This helps to focus on efficiency by using 1×1 bottleneck convolutions and pooling instead of fully connected layers [76]. The bottleneck is for channel dimensionality reduction. Unlike AlexNet that is a sequential model, GoogleNet has a parallel concatenation of networks with 22 layers and 5.98 million parameters. It has 12 times less than the number of parameters in AlexNet.
4. **Xception:** is based on depthwise separable convolution, known as separable convolution [77]. Xception or Extreme Inception involves introducing inception module between the regular convolution and a separable convolution (a depthwise convolution with a pointwise convolution). This concept helps in efficient use of parameters that leads to better performance.
5. **Vision Transformer (ViT):** is based on the commonly used transformer architecture for Natural Language Processing (NLP). Unlike transformer for NLP that uses encoder and decoder, ViT uses transformer encoder followed by multilayer perceptron (MLP) [69]. Before the transformer encoder, the input image is split into a linear fixed-size patches and then added a positional embedding to the sequence including classification token. The transformer encoder has an alternating layer of multi-headed self-attention (MSA) and MLP blocks. This concept is applied here in SC defects classification problems.
6. **Darknet53/YOLOv3:** is one of the variants of YOLO based models that are used for object detection problems. Other variants of YOLO models are YOLOv2, YOLOv4, YOLOs, You Only Learn One Representation (YOLOR), YOLOX, PPYOLOE, YOLOv5 and YOLOv7. In this work, YOLOv3 was employed for the

SC classification, and it uses the concept of residual connection with 3×3 and 1×1 convolutional layers. This is then stacked together to have a total of 53 convolutional layers in the network. It is sometimes called DarkNet-53 [78] because of the 53 convolutional layers.

7. **ResNet:** Residual Network (ResNet) uses the concept of residual blocks that helps address the issue of vanishing gradient with respect to the network's weights in feedforward networks. The gradient in conventional deep learning networks is backpropagated through the previous layers. However, the deeper the deep learning networks, the smaller the gradient. Hence, this can affect the performance of the networks. So, one way of solving this problem was the introduction of shortcut connections to fully connected layers that simply perform identity mapping (known as residual mapping). Some of the common variants of ResNets includes 18,34,50,101 and 152 [79] which have stacks of residual or bottleneck blocks. All five variants were applied in our experiments. The residual block comprises two convolutional layers, and it is used in ResNet18 and ResNet34, while the bottleneck has three convolutional layers for other variants. The bottleneck was introduced to allow faster training time in deeper ResNets variants like ResNet50, ResNet101 and ResNets152.
8. **SqueezeNet:** is a small CNN architecture that has more accuracy compared with that of AlexNet despite having almost 50 times fewer parameters [80]. The aim of the network is to have fewer parameters while maintaining higher accuracy. The architecture used the concept of a fire module consisting of squeezed convolution layer with 1×1 filter, and two, 1×1 and 3×3 , expanded convolution layers.

The squeeze layer helps decrease the number of input channels to 3×3 filters and many of the 3×3 filters are replaced with 1×1 filters. Each replacement accounts for 9 times fewer parameters which then facilitates reduction in the network.

Furthermore, the combination of different models to form a single model offers advantages that are driven by the recognition that different models' collective insights can outperform individual ones. The rationale for combining different models through ensemble methods to form single model is because of a performance accuracy improvement and a substantial boost in predictive inference precision as recommended in [81].

To practically execute this approach, two ensemble techniques, bagging and voting, were applied on the elpv dataset. In the experimentation phase, eight independent models—namely, AlexNet, SENet, GoogleNet, Xception, Vision Transformer (Vit), Darknet53, ResNet18, and SqueezeNet—were chosen as base models or estimators among the twelve selected models. Through these ensemble methods, the goal was to use their collective estimators' strength to improve the overall ensemble model performance. The first method, voting, uses the same batches of dataset for all estimators as inputs, and the estimators acted differently on the dataset as shown in Figure 24. Their performances were then aggregated using soft voting. However, for the bagging methods, each estimator acts on a different batch of dataset, sometimes referred to as bootstrap aggregating. This is because a bootstrapped set is used for the dataset where a new selection of batch dataset can be obtained from the original set with replacement. The performance of the ensemble model was then obtained with the use of either soft or hard voting of the estimators' performances to produce a single performance value. In this study, soft voting was used for both ensemble

techniques, which involves finding the average of the overall performance. Hard voting, on the other hand, uses majority voting for the performance aggregation. For instance, given a Non-Defective (ND) sample SC image that is passed to the five estimators. Each estimator provides performance results on the ND sample SC, and the classification is either ND or D (Defective) as shown in Figure 25. For hard voting, the classification would be ND if there were three votes for ND and two for D because it takes the majority vote. But for soft voting, we can find the average of the performance as calculated in equation (13) and (14). The highest aggregation value, in this case ND, would be the class for the ensemble method. We use the average of the performance results known as soft voting as compared to the hard voting, which uses majority voting for the performance aggregation:

$$ND = \frac{0.6 + 0.8 + 0.9 + 0.3 + 0.4}{5} = 0.6 \quad (13)$$

$$D = \frac{0.4 + 0.2 + 0.1 + 0.7 + 0.6}{5} = 0.4 \quad (14)$$

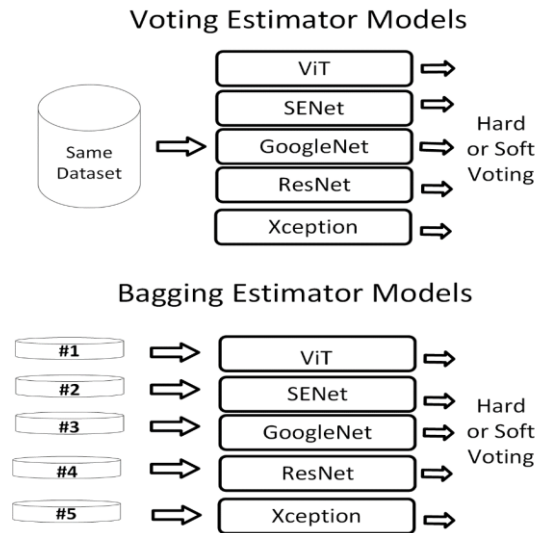


Figure 24: Voting and bagging ensemble methods using batches for the models.

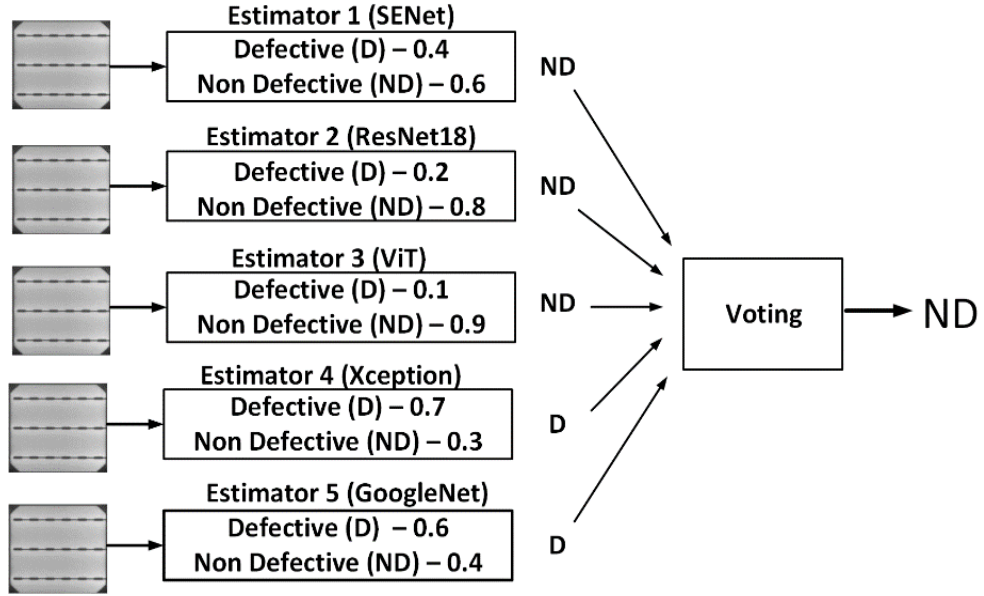


Figure 25: Soft and hard voting aggregation description for the five selected estimators using the defective (D) and non-defective (ND) binary classification.

In summary, this research practically applies twelve selected deep learning models on three different sets of elpv dataset and implementation of two ensemble techniques, bagging and voting. Eight base models or estimators including AlexNet, SENet, GoogleNet, Xception, Vision Transformer (Vit), Darknet53, ResNet18, and SqueezeNet were selected for experiments among the twelve models based on the resources available. These ensemble methods aimed to leverage the collective strength of these estimators to have a single model known as ensemble model for performance improvement.

4.3. Performance Evaluation Results for SC Defects Classification

The study involves applying twelve different deep learning classification models to SC defects dataset, namely elpv-2, elpv-4, and elpv-12. The first experiment involves applying the models on elpv-4 dataset. The accuracy results of these models are presented

in Figure 26, where it is observed that AlexNet achieved the highest accuracy at 67.619%. This result is attributed to AlexNet's simpler architecture with 8 convolutional layers, which tends to perform better with smaller datasets of elpv-4 2,624 number of samples, in comparison to other models [73]. However, the performance accuracy of the other models was increased when applied to the elpv-2 binary classification dataset due to less variants of dataset. For elpv-12, additional datasets with different classes were collected to further improve the accuracy values since the deep learning models used requires large amount of data [82]. This resulted in an improved accuracy performance for all models and shows that Xception model achieved the highest accuracy score of 91.399%.

Similarly, when considering other performance metrics like F1 score, precision and recall, Vision Transformer (ViT) has the highest score of 80.0% for both micro and weighted F1 scores as shown in Figure 27 (a) for elpv-4. The F1 score improved for elpv-12 to 1.0 for the models except AlexNet, ResNet50 and YOLOv3 as shown in Figure 27 (b). This shows that the three low performance models are not recommended for SC defects classification. Also, ViT has the highest performance of 80.0% precision and recall scores, as shown in Figure 28, for elpv-4 dataset for both micro and weighted averages. Considering the results for elpv-12 precision and recall, all the models had an improvement score of 1.0 in the two metrics with the exception of AlexNet, ResNet50 and YOLOv3 like the F1 score results. This means that the augmentation and data balance in elpv-12 is effective to improve the performance of each of the twelve models but, the three low performance models is not suitable for SC defects as compared to other models. Although, there was an improvements in the performance of the three models from elpv-4 to elpv-12, the other nine models are recommended for SC defects problems.

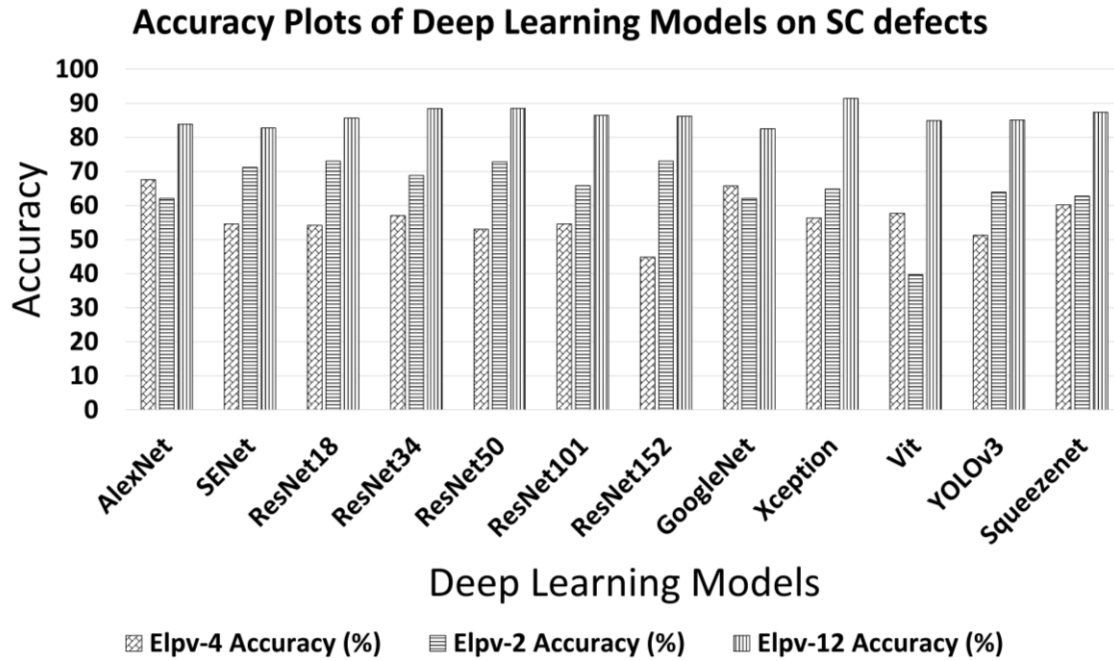
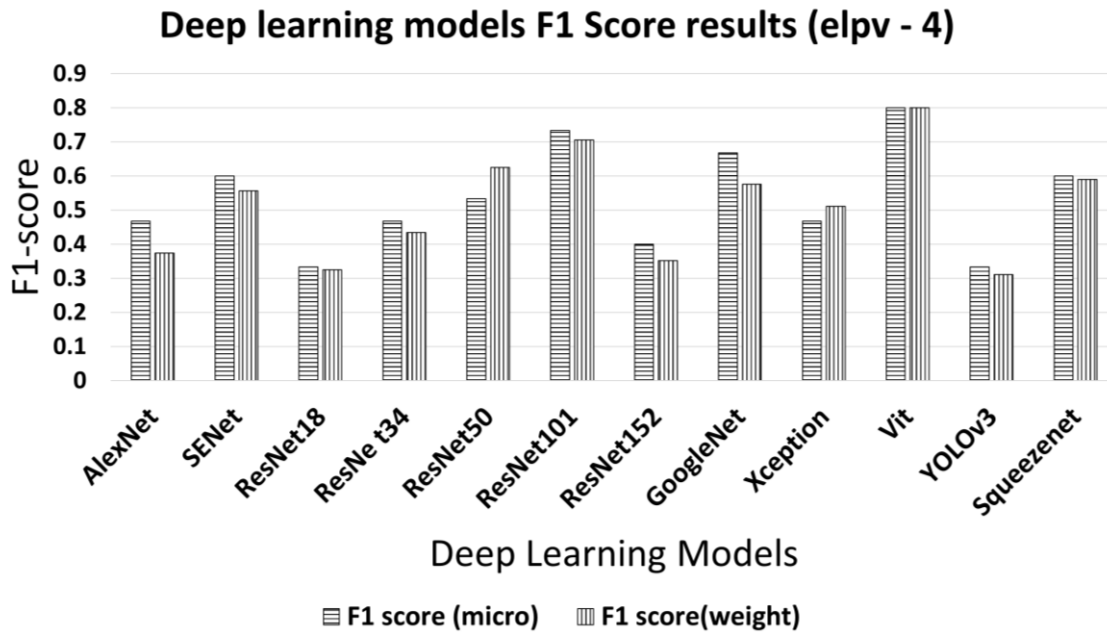
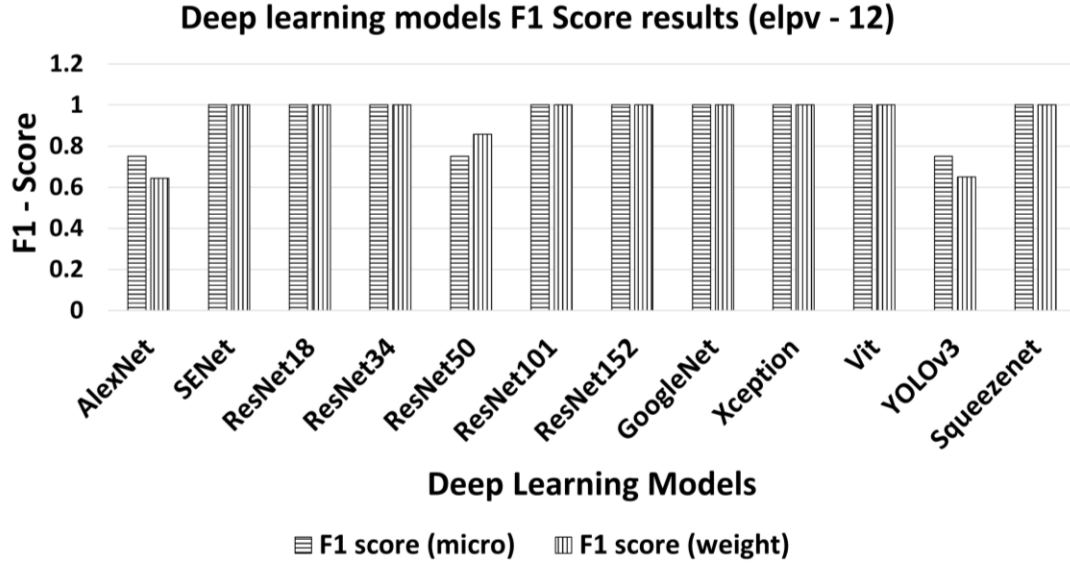


Figure 26: Metrics evaluation for elpv-4, elpv-2 and elpv-12 dataset using accuracy.



(a)



(b)

Figure 27: (a) F1 score (micro and weighted) metrics evaluation for elpv-4 and (b) F1 score (micro and weighted) metrics evaluation elpv-12 dataset with improved performance.

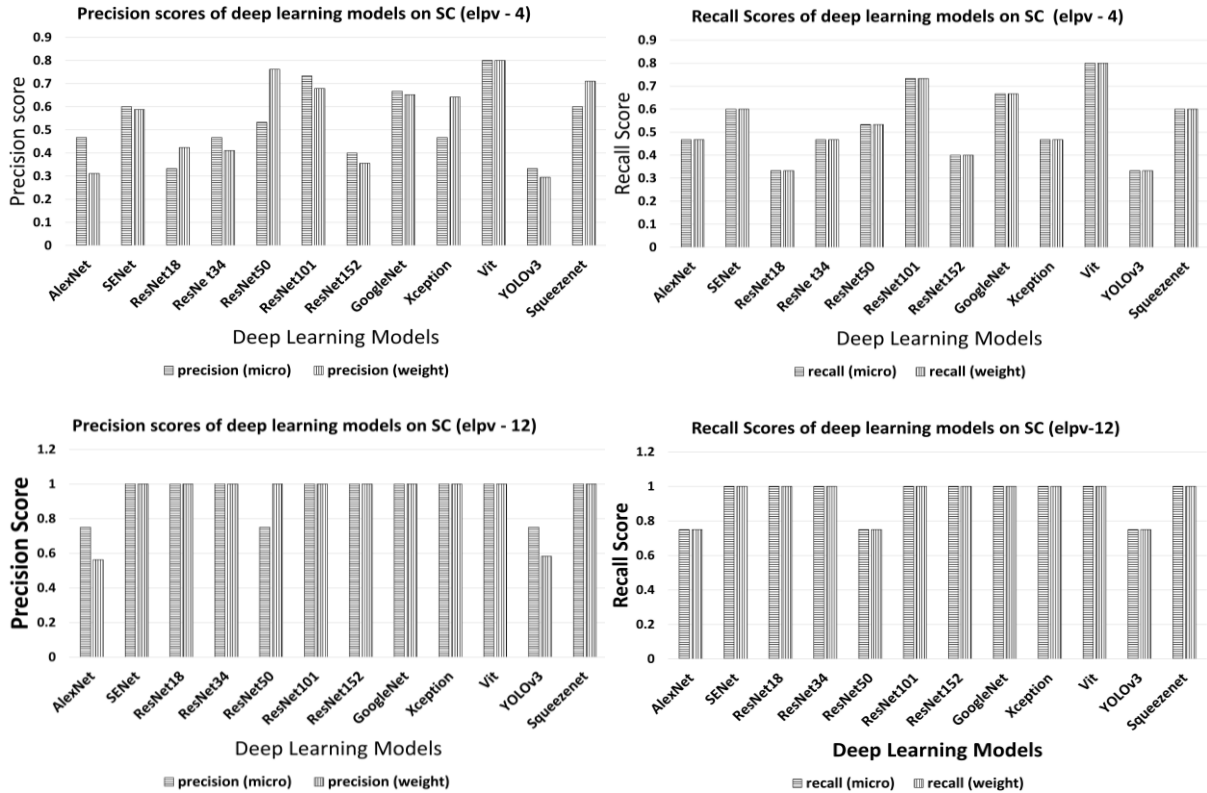


Figure 28: Metrics evaluation for elpv-4 and elpv-12 (ours) dataset using precision and recall for micro and weighted averages on test dataset.

Furthermore, the study involves combining these models using bagging and voting to increase performance accuracy of the models on the elpv dataset. Ensemble methods were applied on both elpv-2 and elpv-4. The experiment using the ensemble method involves combining 8 models: AlexNet, SENet, GoogleNet, Xception, Vision Transformer (ViT), Darknet53, ResNet18, and SqueezeNet to form single model. The results are then compared with individual models. Figure 29 depicts the accuracy scores of the 8 models, including the two ensemble methods, for both the elpv-4 classifications and binary classification. The ensemble techniques have higher accuracy of 68.36% for the voting and 68.31% for the bagging on elpv-4 dataset.

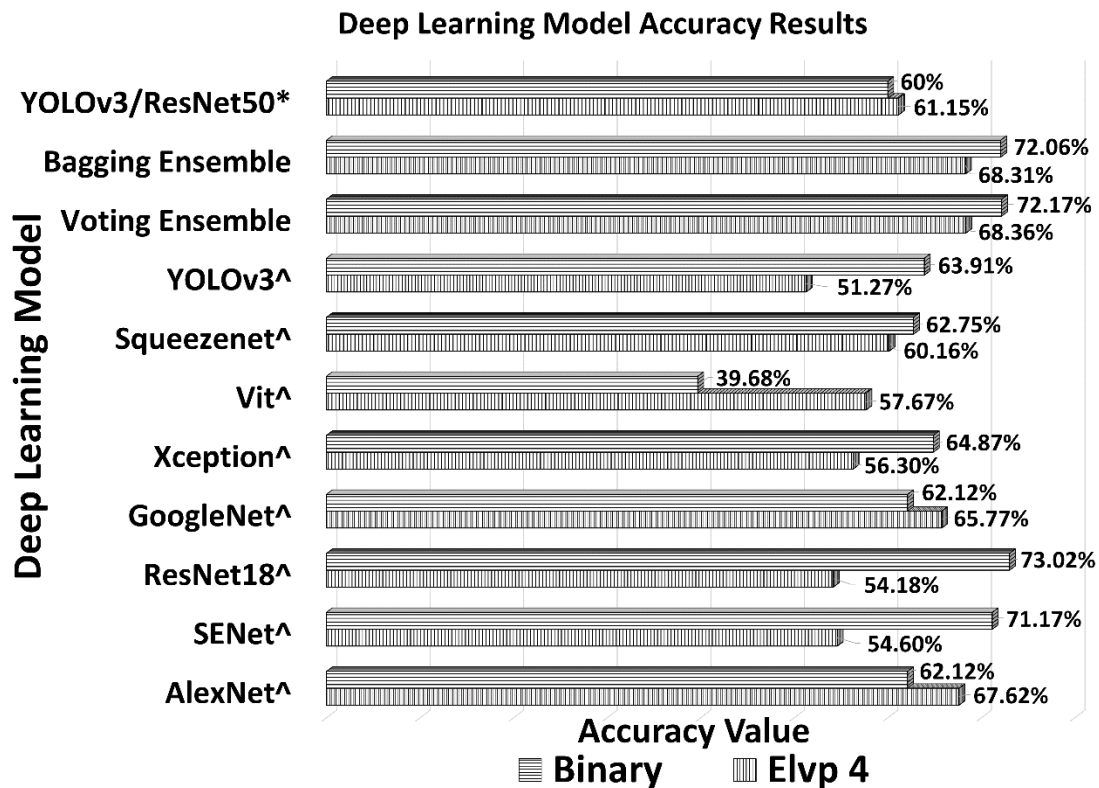


Figure 29: The test accuracy results using the 8 models and the two ensemble methods for binary and elpv-4 classifications. *YOLOv3/ResNet50 results from the paper [29] and ^ indicated individual results

While for elpv-2, voting ensemble is 72.17% and bagging ensemble is 72.06%. However,

ResNet18 has 73.02% which is higher than the two ensemble methods for elpv-2. This shows that instead of increasing the number of classes from 4 in elpv-4 to 8 when performing an ensemble technique on the dataset, it was reduced to 2 in the binary classification of elpv-2. This leads to lower performance accuracy in comparison with the base estimators. From [83], It was recommended to have the same number of classes as the number of models, which is 4 in this case. However, the number of classes should not be more than the number of estimators to have an increment in an ensemble model's performance.

4.4. Training and Validation Process

Similarly, the Google Colab GPU platform was used for training like the SP defect detection. For SC, grid and random hyperparameter tuning were applied for better classification. Hyperparameters are settings that are not learned from the data but are set prior to training and affect the learning process. This set of parameters are given in Table 9 for the three types of elpv dataset.

Table 9: Hyperparameters chosen for classification task.

Hyperparameters	elpv-2	elpv-4	elpv-12
Batch size	16.0	25.0	25.0
Image Resolution	224.0	224.0	256.0
Learning rate	0.001	0.0001	0.0001
Optimizer	Adam	Adam	Adam
Number of epochs	20.0	50.0	50.0

The elpv-4 hyperparameters are the same as that of ensemble methods. However, ensemble has weight decay that is 0.0005 and the learning rate that was decreased as the training progressed using an adaptive learning rate scheduler of the type of Cosine Annealing [84].

CHAPTER 5

CONCLUSION

This research primarily focused on two aspects. Firstly, application of deep learning techniques for detecting defective and non-defective Solar Panels (SPs) in solar PV systems. Secondly, an extension to classification of defects in Solar Cell (SC).

5.1. Summary of Findings

This thesis explored the application of deep learning models in the defect detection and classification for solar photovoltaic (PV) systems. A PV system contains several components including inverter, battery, and SP. But SP is the major component we focused on in the research. SPs also have a variety collection of SCs which are arranged in either 60-cell, 72-cell, or 96-cell per SP. Since SPs must be deployed in outdoor environments to receive sunlight, it is exposed to several unwanted conditions like rain and extreme heat which result in the efficiency loss of the SP. This exposure causes defects on the panels which if not mitigated could further reduce the SP performance over time. Hence, this research work helps in addressing the defective issues in SP and SC in PV systems with the use of deep learning models.

For SP defects detection in solar thermal images, two approaches were used namely, segmentation and detection. The segmentation involves prediction of segmentation mask. These masks were improved with the use of bicubic and bilinear upsampling. On the detection of the defects in SP, two experiments were performed, one involved use of three types of defects, i.e., hotpots, diodes, and junction and the other involved two classes which

are defective and non-defective. This is due to difficulties in distinguishing different types of defects from the given dataset, especially for a large solar power plant. Then, it was realized that the transformer based You Only Look at One Sequence (YOLOS) performs better than other variants of YOLO in the detection of defects in solar thermal images. Furthermore, a developed deep learning model known as YOLOS-PV based on the YOLOS model with the adjustment of weighted values of the Generalized Intersection over Union (GIoU) and L1 losses improved the performance of the system. It was found that W_{L1} (L1 loss weight) of 0.25 and W_{giou} (GIoU loss weight) of 0.75 had better defective result for solar thermal image problems.

Furthermore, the other experiments involved application of twelve different deep learning models namely, AlexNet, SNet, ResNet18, ResNet34, ResNet50, ResNet101, ResNet152, GoogleNet (Inception V1), Xception, Vision Transformer (Vit), YOLOv3, and SqueezeNet for SC defects classification. These models were selected due to their widely used in the literature for problems related to SP defects. Similarly, models like EfficientNet were not selected because of high GPU memory requirement, to train on the collected dataset. Furthermore, the study involved two ensemble methods namely, voting and bagging, which are combinations of different models to form a single model for better classification performance. This study found that voting performed better than the bagging for SC defect classification. The research also emphasized the significance of having extensive labeled training datasets, which played a crucial role in achieving high levels of accuracy. As for the experimental evaluation, this study involved collection of datasets, i.e., elpv-12. Thus, the study found out that among the twelve models selected for the elpv-12 dataset, Xception model achieved the highest accuracy of 91.4% for the SC defects classification.

5.2. Challenges of the Proposed System

The following highlights the limitations of using the proposed methodology for solar defects detection:

1. The number of defective classes considered in this research is limited to 11 for SC which is not enough in comparison with the existing identifiable defects.
2. Similarly, detecting defects in solar thermal images is also limited to defective and non-defective detection which does not take classes like hotspot, diode, and junction into consideration.
3. The system is presently not a real time defects detection using drones. Currently, the system involves collection of image dataset from the drone videos and application of deep learning on the images collected. However, a future system could directly detect the SP defects on the solar plant using drone.
4. The study did not involve the detection process like electroluminescence imaging but only utilized the image dataset collected from such process.

5.3. Contribution of the Thesis

My contributions on the defect detection from SP includes the following:

1. For the SP detection, many researchers have focused on the detection of SP defects on satellite and aerial RGB images on rooftops and façade [42] while not taking account of the defect's detection on thermal images. Similarly, they have focused on single defects detection like hotspot while not considering some of the other defects such as Diode and Junction. I added these defect types to my research work. Although, the inference performance was reduced but gave more room to explore

other kinds of possible defects that affect SP efficiency.

2. I also contributed to the application of segmentation techniques on SP thermal images by exploring two interpolation techniques of Bilinear and Bicubic for mask prediction. This facilitates better region detection of the defects using the object detection models YOLO variants.
3. I contributed to the development of a transformer based YOLOS-PV model that is based on YOLOS model. The YOLOS model has challenges of predicting overlapped bounding boxes of different labels. This is due to lack of implementation of Non-Maximal Suppression (NMS) technique that helps reduce the redundance overlapping bounding box prediction. So, YOLOS-PV was proposed by making the bounding box loss (the combination of GIoU and L1 regression loss) a weighted loss values instead of linear combination of the loss.

My contributions on the SC defect classifications include the following:

1. Firstly, the dataset available for SC defects classification in the literature [85] is limited to 2,624 based on what deep learning models can train. So, I collected a second dataset of 18,347 from publicly available dataset with 11 defects including non-defective classes [86].
2. Researchers have used at most three deep learning models for detecting SC defects. However, in this work I applied twelve different deep learning models (AlexNet, SENet, ResNet18, ResNet34, ResNet50, ResNet101, ResNet152, GoogleNet (Inception V1), Xception, Vision Transformer (Vit), YOLOv3, and SqueezeNet) on both datasets and compared the performance.

3. I also applied an ensemble technique to combine the models and compared the performances with that of individual techniques. To my knowledge, I have not encountered the use of ensemble techniques for classifying SC defects in the literature due to the small number of models utilized for the process.

5.4. Future Directions for Improvement and Extension

To improve the performance of the proposed deep learning system for the detection of SP and classification of SC defects, further research could explore the variation of defects in different SP plants. Obtaining more accurate and comprehensive data from industry could help refine the models and improve SP defect detections. Additionally, optimizing the weight values of L1 and GIoU during training using methods such as gradient descent could lead to better SP defect detection accuracy and faster convergence for the proposed model YOLOS-PV. Future research could also explore the application of the YOLOS-PV model to other domains by fine-tuning the weights hyperparameters. However, further experimentation and research will be required to determine the effectiveness of the deep learning system in different domains. Deployment techniques for the models on the drone is a great exploration for future research purposes. This could ensure a more reliable defects detection through real time process by combining the deep learning techniques such as classification, segmentation, and detection all in a drone operating system.

Appendices

A. Theoretical Research on Real Time detection

The theoretical research is on the deployment process of models on drone OS specifically UAVIA DroneOS [75]. Since the UAVIA has a robotics platform as shown in Figure 30, the deployment tends to be done through this platform. The models will be converted and optimized using Nvidia's TensorRT due to capability to manage inference applications [76]. The deep learning models such as Xception architecture can then be implemented using TensorFlow or PyTorch framework and converted to TensorRT before deployment. The converted TensorRT framework can also be done through UAVIA support. In the study, it was realized that among the list of processors in drones such as Intel Movidius, ARM and Nvidia's Jetson TX2, the latter is more compatible for machine learning deployment on the drone. The models will utilize this processor when performing training actively on the drone. The trained deep learning can be pulled by UAVIA and then containerized it and pushed it using the drone processors. Note that TensorRT does not directly perform inference from PyTorch or TensorFlow frameworks. It needs to be transformed into a Universal File Format (UFF). However, TensorRT has no implementations for model architectures. So, a TensorRT plugin is given for the missing functionality. The resulting UFF model file will then be loaded in TensorRT for inference. Although TensorRT can parse a UFF model, it also performs hardware optimizations. For instance, it combines multiple layers into a single Cuda kernel which gives rise to increased memory bandwidth, and then selects the kernels that perform best on the target hardware.

This is referred to as the TensorRT engine model. This engine is the final form of the model to be used on drones for optimum performance. The engine is then packaged and deployed to the model library on the server.

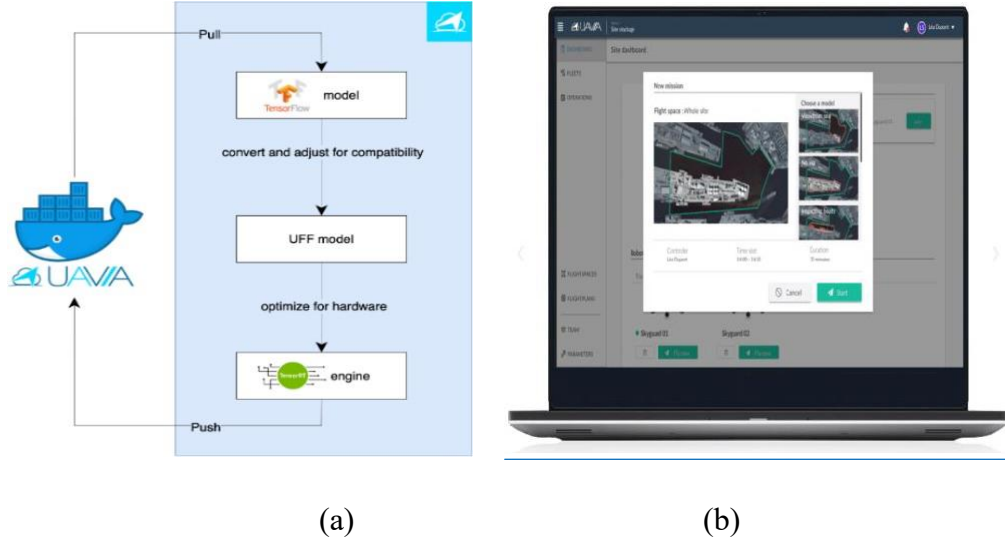


Figure 30: (a) UAVIA optimization pipeline for TensorRT (b) UAVIA Drone OS User Interface [75]

B. Code Implementation Details

The code documentation has been provided on the Github and Google Colab repository. Code Implementation for Solar Panels: Segmentation [87] , YOLOS-PV Detection [88], YOLOv5 – Three classes [89], YOLOv5 – Single class [90], YOLOv6 [91], YOLOv7 [92], YOLOv8 [93], YOLOS [94]. Code Implementation for Solar Cell: Classification [95] and [96]. Ensemble Method [97].

C. Platform Implementation and Comparison

A platform was developed to evaluate the quality of detecting and classifying the defects in both SC and SP thermal images. The platform is shown in Figure 31 which has classification, segmentation, and detection sections. The classification is divided into cell and panel while detection is for the single and multi-defects detection. The platform experimental output is then compared with the Nanonets [54] platform which is shown in Figure 32.



Figure 31: Platforms developed for the thesis to compare the results with the Nanonets [54] platforms. Page 1 (hambal-thesis.azurewebsites.net)

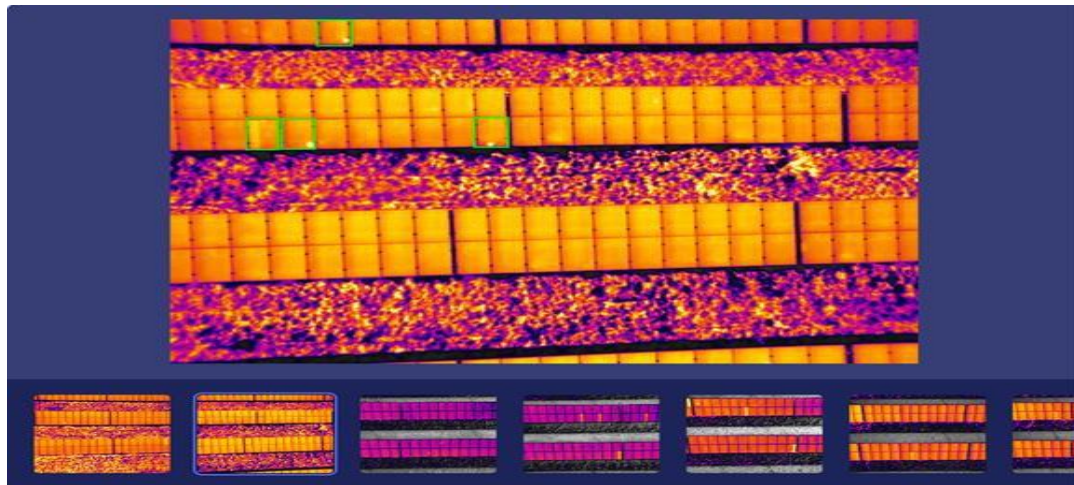


Figure 32: Nanonets Sample platform for 8 Images

The average accuracy for the Nanonets platform is 98.9% for 8 images while the average accuracy is 94.0% for 372 images in the thesis platform for detection of single defect.

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Vitae

Name : TELLA HAMBAL BABATUNDE

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Address : 6, Adekoya Street Itire-Ikate, Lagos, Nigeria. 101283

Academic Background :

Education

MSc KFUPM Electrical Engineering, Saudi Arabia Aug 2021-Sept 2023

BSc Obafemi Awolowo University Ile-Ife, Osun, Nigeria Jan 2011 -Aug 2017

Studied Electrical Engineering.

Honors and Awards

KFUPM Graduate Assistant Scholarship Aug 2021

Full scholarship awards that cover: Tuition, Books, Accommodations, and Conference

INDABAX-AI4D Innovation Grants Oct 2020

Awarded grant for: ChexNet Model Compression for Pneumonia Detection using Low Powered Edge Devices.

Etisalat Merit Award Scholarship Nov 2014

Scholarship Award for best student in the class, in third year of my Undergraduate.

Publications

Conference Papers Published

H. Tella, M. Mohandes, B. Liu, S. Rehman and A. Al-Shaikhi, "Deep Learning System for Defect Classification of Solar Panel Cells," 2022 14th International Conference on Computational Intelligence and Communication Networks (CICN), 2022, pp. 448-453, doi:10.1109/CICN56167.2022.10008277.

Code Implementation: [tella26/Panel-Defects- \(github.com\)](https://github.com/tella26/Panel-Defects)

H. H. Nuha, R. R. Pahlevi, M. Mohandes, S. Rehman, A. Al-Shaikhi and H. Tella, "Vertical Wind Speed Estimation Using Generalized Additive Model (GAM) for Regression," 2022 14th International Conference on Computational Intelligence and Communication Networks (CICN), 2022, pp. 691-695, doi:10.1109/CICN56167.2022.10008372.

Conference Papers Accepted

[Tella, H.](#) Mohandes, M. Al-Shaikhi, A. Liu, B. Rehman, S. and Nuha, H., "Bagging and Voting Deep Learning Ensemble Methods for Binary Classifications of Solar Panel Cells Defects" 20th International Multi-Conference on Systems, Signals & Devices (SSD), Feb. 20-23, 2023, PAPERID-1570868989.

Research Experience

Unpublished - Term project papers in my graduate courses.

1. Title: [Semantic Segmentation Model Design for Understanding Satellite/Drone Images](#)

KFUPM, Dhahran

December 2022

Advisor: Dr Hamzah Luqman – ICS 590

- SETR, Segmentation, SegFormer, UNet and Semantic.

2. Title: [Exploring Seismic Data Interpolation using Radial Basis Function](#)

KFUPM, Dhahran

April 2022

Advisor: Professor Wail A. Mousa – EE 562

- Radial Basis Function, Interpolation and Signal Processing

3. Title: [Analyses of Top-Gated Carbon Nanotube Field Effect Transistor using the New Perspective](#)

KFUPM, Dhahran

December 2021

Advisor: Dr Feras Al-dirini – EE 608

- Nanoelectronics, Graphene and Carbon Nanotube.

4. Title: [Markovian Model for the Analysis of Age of Information in IoT Networks](#)

KFUPM, Dhahran

December 2021

Advisor: Dr Suhail I. AL-Dharrab – EE 570

- Stochastic process, Markovian Model and IoT

Teaching Experience

1. **KFUPM**, Dhahran, Saudi Arabia August 2022 to December 2022

Co-Supervised Senior Students Project, Electrical Department

Title: **Vertical and Horizontal Wind Speed Forecasting using LP/CNN/ResNet**

Supervisor: Professor Mohamed Mohandes

- Co-Supervised for Deep Learning and Time series forecasting for EE 411-7, Term 221

2. **KFUPM**, Dhahran, Saudi Arabia August 2021 to May 2023

Teaching Assistant, Electrical Department

- Laboratory Instructor for EE 371 (Communication Lab) Term 212
- Digital Systems Engineering EE-390-11 Term 222
- Probabilistic Methods EE-315-09 Term 221
- Probabilistic Methods EE-315-02 and EE-315-03 Term 222
- Applied Digital Signal Processing EE-413-01 Term 222

3. **First Technical University**, Ibadan, Nigeria

June 2018 to March 2020

Teaching Assistant, Electrical/Electronic Department

- Prepared and reviewed Laboratory Manuals for Electrical Engineering Department.
- Assisted the lecturer in preparation of course materials for EEE 201/207 and course tutorials.
- Supported lecturer in class, marked test and exams scripts, and ensured compliance in the Laboratories.
- Assisted the lecturer in the preparation of application for grants.