DETECTION OF FAULTY SOLAR PANELS USING ARTIFICIAL INTELLIGENCE TECHNIQUES

2024
MASTER THESIS
ELECTRICAL AND ELECTRONICS ENGINEERING

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Prepared as
Master Thesis

KARABUK

August 2024

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Asmail Abrahim FANIAR

ABSTRACT

M.Sc. Thesis

DETECTION OF FAULTY SOLAR PANELS USING ARTIFICIAL INTELLIGENCE TECHNIQUES

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August 2024, 53 pages

Artificial Intelligence (AI), including Deep Learning (DL) and Machine Learning (ML) techniques, has shown exceptional effectiveness in identifying defective photovoltaic (PV) panels through image classification. This thesis presents an approach for classifying malfunctioning solar PV panels utilizing Convolutional Neural Networks (CNNs) to extract features from images of defective and non-defective panels. Metaheuristic approaches, such as Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), are then employed to select the most indicative features, enhancing the accuracy and reliability of fault detection. The extracted features are classified using various ML algorithms, including decision tree (DT), support vector machine (SVM), K-Nearest Neighbor (KNN), ensemble methods, and discriminant analysis. The model was trained on a dataset with four defect rate classes: 0%, 33%, 66%, and 100%. The applied algorithms achieved accuracy rates of 94.88%, 76.20%, 97.45%, 98.34%, and 80.23%, respectively. This research demonstrates good improvements in fault detection, offering practical implications for maintenance and optimization of solar PV systems.

Keywords: Faulty Solar Panel, Artificial Intelligence, Machine Learning Methods
Science Code : 915.1.092

ÖZET

Yüksek Lisans Tezi

YAPAY ZEKÂ TEKNİKLERİYLE ARIZALI GÜNEŞ PANELLERİNİN TESPİTİ

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Dr. Öğr. Üyesi Cihat ŞEKER
Ağustos 2024, 53 sayfa

Derin Öğrenme (DÖ) ve Makine Öğrenme (ML) teknikleri de dahil olmak üzere Yapay Zeka (AI), görüntü sınıflandırması yoluyla arızalı güneş panellerin belirlenmesinde olağanüstü etkinlik göstermiştir. Bu tez, arızalı ve arızasız güneş PV panellerinin görüntülerinden özellikler çıkarmak için Konvolüsyonel Sinir Ağları (CNN'ler) kullanarak arızalı panellerin sınıflandırılmasına yönelik bir yaklaşımı sunmaktadır. Ardından, en belirleyici özelliklerin seçilmesini artırmak için Parçacık Sürüsü Optimizasyonu (PSO) ve Karınca Kolonisi Optimizasyonu (KKO) gibi metaheuristik yaklaşımlar kullanılmaktadır. Çıkarılan özellikler, karar ağacı (DT), destek vektör makinesi (DVM), K-En Yakın Komşu (KNN), topluluk yöntemleri ve ayrım analizi gibi çeşitli ML algoritmaları kullanılarak sınıflandırılmıştır. Model, 0%, %33, %66 ve %100 olmak üzere dört arıza oranı sınıfından oluşan bir veri seti ile eğitilmiştir.

Uygulanan algoritmalar sırasıyla %94.88, %76.20, %97.45, %98.34 ve %80.23 doğruluk oranlarına ulaşmıştır. Bu araştırma, arıza tespitinde önemli iyileştirmeler sağladığınıve güneş PV sistemlerinin bakım ve optimizasyonu için pratik anlamlar sunduğunu göstermektedir.

Anahtar Kelimeler: Arızalı Güneş Paneli, Yapay Zekâ, Makine Öğrenimi Yöntemleri

Bilim Kodu **:** 915.1.092

ACKNOWLEDGMENT

First of all, I would like to give thanks to my advisor, Assist. Prof. Dr. Cihat ŞEKER, for his great interest and assistance in the preparation of this thesis.

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SYMBOLS AND ABBREVIATIONS INDEX

AI	: Artificial Intelligence
ML	: Machine Learning
DL	: Deep Learning
ACO	: Ant Colony Optimization
PSO	: Particle swarm optimization
ANN	: Artificial Neural Network
CNNs	: Convolutional Neural Networks
EL	: Electroluminescence
PID	: Potential-Induced Degradation
GLCM	: Gray-Level Co-Occurrence Matrix
KNN	: K Nearest Neighbor
DT	: Decision Tree
PV	: Photovoltaic
SVM	: Support vector machines
BAFPN	Bidirectional Attention Feature Pyramid Network
RPN	: Region Proposal Network
LCOE	: Levelized Cost of Electricity
ROI	: Return on Investment
IoT	: Internet of Things

PART 1

INTRODUCTION

The swift growth in the utilization of solar energy is attributed to the escalated requests for clean energy [1,2]. As the number of solar photovoltaic installations rises, the assurance of effective performance by detecting potential operational faults becomes crucial. Malfunctioning PV panels can significantly impact their functionality, resulting in diminishing power output and the possibility of safety risks. Consequently, developing robust and effective methods for finding defective PV panels is vital [3,4].
In recent years, solar PV systems have emerged as a substantial participant in the global transition towards sustainable energy, offering an eco-friendly alternative to conventional fuels. However, despite their potential to revolutionize energy production, PV solar modules are vulnerable to several faults and anomalies which compromise their effectiveness [5,6].

Maintaining the dependability and effectiveness of solar PV systems depends critically on identification of faulty solar PV panels. Conventional techniques of fault identification are normally based on manual inspection or periodic maintenance routines, that can be labor-intensive, laborious, and liable to human error. As solar installations proliferate and expand, the necessity for automated fault detection approaches is paramount [7,8].

The integration of AI techniques in solar PV fault detection, has several advantages over traditional methods [9–11]. These methods can discover the patterns in the data which reveal minute anomalies that lead to underlying problems which are difficult for humans to detect. Furthermore, when more data is gathered, and algorithms are

improved, AI-driven systems can improve over time, enhancing fault diagnosis' accuracy and dependability.
The successful implementation of AI-based fault detection systems has the potential to revolutionize the operation and maintenance of solar PV, minimizing downtime, optimizing performance and reducing operational costs [12]. By advancing our understanding of solar panel diagnostics through interdisciplinary research at the intersection of renewable energy and AI, this thesis helps to advance technology for sustainable energy and fosters the broad utilization of solar PV systems as dependable and clean energy for generations to come.

CNNs demonstrate good performance for processing data which involving images. CNNs automatically extract features from images by employing multiple layers (convolution and pooling), mimicking the human brain. Classification tasks for images, such as analysis of medical imaging, object and facial recognition, have demonstrated success with this technique [13].

Numerous researches explored the use of CNNs for detecting faults in PV solar system. Regardless of these remarkable efforts, significant challenges remain in developing a reliable and precise fault detection technique. The absence of a carefully selected dataset of defective solar PV panels is the major obstacle. A comprehensive and varied dataset is essential to train and test the models, but obtaining the aforesaid dataset is difficult, as available ones are little and have a narrow focus.

The PV energy market has experienced significant growth recently due to cost reductions, technology breakthroughs and growing awareness of environmental benefits. Market dynamics, policy support and innovation all influence the solar PV industry's economic environment [14].
PV module prices have dropped by about 90% over the past decade thanks to improved manufacturing and better solar PV performance. The economic indicators, such as Levelized Cost of Energy (LCOE) continues to decline, making it one of the most cost-effective new electricity generation sources, cheaper than fossil fuels and other renewable sources [15]. Also, the Return on Investment (ROI) and Payback Period indicators have improved (substantially less than ten years), making PV in-

vestments attractive to residential and commercial customers [16]. Moreover, the installation, inverters and other components have also seen cost reductions, further decreasing overall PV installation expenses.
Solar PV systems have low maintenance and operation costs compared to other energy sources, making them economically favorable in the long term [15].
The PV energy economy is strong and improving. Technological progress, cost reductions and supportive policies drive widespread adoption, making PV energy a competitive and appealing option.

Solar photovoltaic (PV) systems encounter different issues that can affect their performance and longevity. One significant issue is soiling, where debris such as dust, dirt and bird droppings can build up on the surface of solar panels, decreasing their effectiveness. Additionally, module degradation occurs as solar panels are exposed to environmental elements leading to a natural efficiency decline over time, typically ranging from 0.5% to 2% per year. Inverters, wiring and connectors can also fail or degrade over time, affecting the overall system performance. The panels' output can be greatly decreased by shadows thrown on them by trees, structures or other obstacles. Also, thermal issues have a big effect on solar PV systems and can lower their efficiency and the lifespan. Lastly, mechanical damage such as scratches, cracks or other physical damage caused by humans while installation and maintenance activities or cause by the weather can diminish solar PV's output [17].

Tracking real-time data, analyzing performance and detecting faults in solar PV systems are crucial tasks for operational efficiency, enhanced maintenance and proactive decision-making.

String monitoring systems, such as the SMA Sunny Tripower, continuously track the current and voltage output of individual strings of solar PV panels to identify underperforming strings or faults. String monitoring systems help in the early detection of defects like shading, soiling, or component failures by offering comprehensive, real-time data. Furthermore, advanced technologies with complex analytics and remote monitoring capabilities, such as the SMA Sunny Tripower, improve solar power system and maintenance even further [18].

Module monitoring systems, such as SolarEdge Power Optimizers and Enphase Microinverters track the output of individual solar modules, which improves solar PV performance and management. By precisely tracking each panel's performance, these systems can identify underperforming units and particular problems like soiling, shading, or component failures. Through data transmission to a central inverter, SolarEdge Power Optimizers are DC/DC converters that maximize each panel's power production. On the other hand, Enphase Microinverters provide precise control and optimization for every panel by converting DC to AC at the section level. These solutions use comprehensive real-time data and analytics to guarantee maximum energy harvest, enhance system reliability and streamline maintenance [19].

Centralized monitoring platforms such as ABB Aurora Vision and Fronius Solar.web offer Solar energy system management and monitoring solutions. Users can remotely access comprehensive analytics and reports to maximize efficiency and maintenance, and they facilitate real-time tracking of energy output and fault identification [20,21].

Software for performance monitoring and diagnosis such as PVsyst, Solar-Log, etc. these software packages provide detailed performance analysis, identification of defects and maintenance planning capabilities [22].

Companies are creating artificial intelligence (AI) for predictive maintenance to identify and anticipate possible faults before they arise, improving system reliability [23].

The integration of IoT devices with solar PV systems enhances real-time monitoring and control capabilities [24], while drone-based inspections using thermal imaging cameras and other sensors efficiently inspect large solar farms [25].

Blockchain technology offers promising solutions for decentralized solar PV networks by facilitating peer-to-peer energy trading, secure transactions and improved grid management [26].

The long-term functionality and efficiency of solar photovoltaic systems depend heavily on effective maintenance. The ability to identify and promptly address maintenance issues is being facilitated by advancements in monitoring systems, like artificial intelligence, IoT and drone technologies. To optimize the efficiency and dependability of solar PV systems, these technologies will become more and more significant as they advance [27].

1.1. PROBLEM STATEMENT

Detecting defective panels in large-scale PV farms can be very difficult and pose challenges. Traditional fault detection methods are impracticable in solar PV farms, because often rely on manual inspection or periodic maintenance routines, which are labor-intensive, time-consuming, high cost and prone to human error. Additionally, the complex patterns of Solar PV cells might elude human detection of hidden and underlying faults.

Recently, renewable energy is a significant topic throughout the globe, with solar PV systems being among essential sources of renewable energy. However, finding defective PV panels in a large number of modules poses challenges. The motivation of this study is to detect faulty solar panels in large-scale PV farms where conventional methods are inadequate.

1.2. OBJECTIVES

To develop robust models for detecting and classifying faulty solar panels in large solar PV farms, utilizing advanced Artificial Intelligence (AI) techniques tailored to the unique characteristics of solar PV panels.
To utilize Convolutional Neural Networks (CNNs) and various machine learning algorithms to classify faults and thoroughly evaluate the accuracy of PV fault detection, with an emphasis on identifying underlying faults that cannot be detected by visual inspection or traditional methods, thereby minimizing downtime and improving system reliability.

1.3. CONTRIBUTION OF STUDY

Using metaheuristics techniques like PSO and ACO to extract the most informative features from EL images and use different ML algorithms to identify faulty and non-faulty panels is the primary contribution of this work.

1.4. THESIS OUTLINE

The thesis is structured to comprehensively address the challenges and innovative solutions in solar panel fault detection. It begins with an introduction presenting the research problem, objectives and significance of using AI in this domain. next the literature review explores existing methods and highlights the limitations of traditional approaches setting the stage for AI-based solutions followed by methodology details the design and implementation of the AI models including data preprocessing and system integration after that results and findings presents the outcomes of the experiments demonstrating the effectiveness of the proposed approach. Finally, the conclusion and future work section summarizes the key insights and suggests potential areas for further research and development.

PART 2

LITERATURE REVIEW

Many AI techniques have been investigated for solar PV panel failure detection. Methods such as neural networks, decision trees, random forests and support vector machines (SVM) are among them [28,29][9]. Although each approach has pros and cons, researchers have investigated the best ways to combine model topologies, feature selection techniques and algorithms to improve fault detection performance.

PV farms have been at the forefront of renewable energy production since their introduction in 1982. The growing use of PV plants worldwide puts them among the most significant renewable energy sources. In 2022 [30], the installed capacity of PV worldwide was 1046.614 Gigawatt Research has explored ways to enhance the integration of PV electrification facilities [31–34]. However, more concentration should be applied to solving how to keep PV plants in service especially during the faults event.

Solar PV plants are prone to malfunctions that may impair their functionality. These faults may happen due to various causes as discussed in [35]. Depending on the type of fault these issues can lead to reduced efficiency and reliability, as well as potential component damage. Arc faults, line-to-line faults and ground faults can increase fire risk. Ensuring PV services operate as effectively and reliably as possible requires addressing these challenges. It is requisite to early detect and address these faults. However, traditional protection systems do not cover the detection of all PV faults. Standard data classification algorithms are often insufficient or unsuitable for recognizing faults within PV farms. Training is the first step in fault detection, coming next testing and then the evaluation of the model's efficacy. Based on time-related characteristics, defects in solar PV systems are of two types: temporary defects and permanent defects. Prompt identification and repair of these defects are essential to keeping the PV plant operating continuously and preventing failures. PV panels often encounter ground faults or line-to-line faults, which are associated with arcs [6][36]. Many solutions were proposed to address these matters. Certain methods of detection are made to detect faults in components of on-grid solar PV systems, covering sub-surface energy collection cable systems, PV array systems and power converters [37].

ANN-based defect detection has been suggested for solar PV systems [38] however comparing several detection methods to ascertain which one works better has not done. Faults which included open circuit and short circuit in solar PV arrays were identified utilizing current and voltage limits [39], Though this method proves inaccurate as PV panels subject to irradiance which constantly changing. Additionally, the existence of protection diodes complicates PV array fault detection as they do not account for problems developing over time. Faults were computed based on PV array's Thevenin equivalent resistance by using currents, voltages, temperature and irradiance [40]. A detection method identified series arc faults using the cross-correlation technique however, shunt defects were excluded [41]. The defect recognition method was limited to addressing problems with overcurrent defensive relaying, that had difficulties identifying line-to-line faults in photovoltaic systems [42].

The paper [43] uses a dataset consists of 20,000 images type infrared to propose a deep learning methods for identifying faults in PV system. The research places an emphasis on integrating and preprocessing the data to enhance the categorization. The suggested approach employs LIRNet and LWCNN, that surpasses many modern artificial neural network models. Compared to other models, LIRNet model obtains a substantially higher accuracy rate of 89.1%. However, the achieved accuracy is 89% is not viable to implement in practical applications, The recognition accuracy needs to be enhanced to at least 95%. Furthermore, the current method struggles to detect underlying faults such as minor cracks, PID, age degradation, etc. Addressing these limitations is essential to guaranteeing the dependability and effectiveness of this approach. The paper [44] presents an approach that uses string measurement data to categorize defects in PV plants. By utilizing drones equipped with thermographic camera to identify faults and the results were cross checked with measured data of string, 74.0% was the accuracy rate.

Paper [45] describes a feasibility investigation to find defective solar cells using a pipeline that processes EL images and applies CNN to classify the images. The used dataset consists of 98,280 labeled images derived from 1,366 modules, with a class distribution showing just 3.4% of the cells belonging to the defective class. The study addresses the problem of imbalanced data and compares several approaches, achieving binary classification problem with BER of 7.73%. The pipeline includes image preprocessing steps using OpenCV and the Keras framework for implementing and evaluating the CNN architecture, with experiments comparing the effects of data augmentation and minority oversampling on the dataset.

The paper [46] proposes an automated method for locating faults in PV arrays using artificial intelligence. The authors evaluate different feature descriptors, classifiers, and weighting strategies, and compare the performance of a linear SVM and a CNN. A dataset of 2,624 images of solar cells was utilized in the study, which were obtained from images of monocrystalline PV modules. The VGG feature descriptor was found to be the most effective, and KAZE/VGG was identified as the top-performing classifier. CNN exhibited superior performance compared to the SVM, achieving 88.42% accuracy on average, whereas the accuracy of SVM was 82.44% on average. The authors report detailed performance of their models on certain solar cell types and show that both models perform better when the number of training samples is increased.

The paper [47] exhibits a framework for detecting faults in PV solar system employing EL imaging. The used dataset consists of mono and polycrystalline PV images. The offered framework uses isolated deep learning approach and a six-layer CNN architecture. Augmentation techniques are employed to extend the small training dataset. The model is trained for 150 epochs using four-fold cross-validation and achieves an average accuracy of 93% having standard deviation of 0.37%. Other metrics for performance like F1 score, recall, and precision are also reported. The suggested structure can be extended to be utilized with other imaging techniques and can achieve even higher accuracy with larger datasets. The paper [48] proposes a CNN model for classifying and detecting defective solar PV panels utilizing electroluminescence images. The used dataset in this research consists of 1800 EL images illustrating four distinct kinds of module conditions: healthy, minor crack, sever crack (broken), and finger interruption. experiments were conducted to assess the methods of data augmentation with the existing machine learning approaches. The findings show how the combined method of generative adversarial networks (GAN) and traditional image processing generates the best performance with an accuracy of 83%.

This paper [49] describes a method for generating physically relevant labels of defects and detecting them using a deep CNN in inline measurements of solar cells. The study uses a dataset of approximately 6,800 mc-Si and high-performance mc-Si wafers from ten different manufacturers. The CNN achieved 88% precision and 91% recall for j_o faults, and 78% precision and 86% recall for Rs faults. The paper highlights how this prediction method is applicable to identifying and monitoring systematic and physically relevant defects.

The paper [50] discusses a weakly supervised semantic segmentation technique to determine cracks in solar PV panels utilizing electroluminescence images. 2624 EL images of solar PV panels were used with expert annotations showing the probability of the faults existing. The authors manually added annotations for the type of defect, focusing only on cracks. A residual network with 50 layers and a normalized Lp layer was employed, and activation maps were aggregated into single scores for classification. The study highlights the importance of selecting the appropriate norm for the given problem to obtain high-quality segmentation results using weakly supervised learning. The best performing norms were found to be L1 and L3, with an accuracy of 0.94.

This paper [51] presents a deep CNN architecture for categorization of faulty solar PV modules using aerial images taken by an unmanned aerial vehicle (UAV). The used dataset contains 2000 images of solar PV modules with various visible defects, including snail trails, dust shading, encapsulant delamination, glass breakage, and others. The authors altered the input on the network by randomly choosing many patches from the source images and increasing the quantity using a mirrored process to generate features with more rotation invariance. The features were taken out of the fully connected layers after the dataset was split into training and testing subsets. The authors achieved an accuracy of 90.23% for the classification of good and bad conditions of PV modules and an accuracy of around 80% for the classification of different defects. The proposed method outperformed CNN that was not pre-trained and the Vgg16 network that was. The paper [52] proposes a new method that uses both short and long term deep characteristics to find microcracks in solar PV panels. The method is tested on two datasets, MCOM and ELPV, and is shown to be effective in detecting micro-cracks in both objective and subjective evaluations. The proposed method achieves a precision, recall, and F-measure of 0.3478, 0.7189, and 0.4688, respectively, on the MCOM dataset, and outperforms other methods on the ELPV dataset in detecting microcracks. As demonstrated by the objective assessment, the suggested approach performs better than approaches that rely solely on previous knowledge or present view information, especially shallow learning-based methods. The subjective evaluation demonstrates that the proposed method can detect both common and block texture micro-cracks.

In the study [53], a modern BAFPN for multi-scale fault identification tasks in raw PV cell EL pictures is presented. BAFPN combines with RPN in Faster RCNN+FPN. With the help of an attention-based top-down and bottom-up architecture, BAFPN combines multi-scale characteristics, and the suggested BAF-Detector performs well in multi-scale defect detection tasks while being robust to scale. In unprocessed EL images of solar PV cells, the proposed technique obtains high F-measure, mAP, and IoU for multi-scale defects classification and identification, according to the extensive EL dataset's experimental findings with 3629 photos, including 2129 faulty ones. In particular, the BAF-Detector produces results of 73.29% (IoU), 88.07% (mAP), and 98.70% (F-measure).

A study on the use of binary and multiclass classification of EL image data for real-time health evaluation of PV solar cells is presented in paper [54]. 2,624 picture samples of both healthy and defective PV cells make up the dataset, which is divided into four groups according to the likelihood of a defect. The work suggests feeding hand-crafted features for data representation, such as local binary patterns (LBP) and Gray-Level Co-Occurrence Matrix (GLCM), to task-oriented, lightweight, and deep feed-forward ANN models as well as bespoke CNN deep architectures. For multiclass classification, the suggested CNN-based customized model achieves state-of-the-art classification accuracy of 83.5%.

This study [55] proposes a method for classifying PV cell images using a dataset of 2624 individual cell images. Due to the limited amount of data available, in this work, transfer learning is employed using deep convolutional neural networks. Pre-trained networks, including AlexNet, GoogleNet, MobileNetv2, and SqueezeNet, are fine-tuned on the dataset using a GPU, enabling each training session to be completed in under an hour. The method achieves a validation accuracy of over 75%.

A technique for PV system defect detection based on low-frequency inverter measurements and satellite weather data is presented in this work [56]. Using a recurrent neural network, this method identifies six distinct defect categories, derived from the past 24h of records, Additionally the model evaluates the drop in output power caused by the defect, thereby assessing fault severity. Achieving 96.9% ± 1.3% accuracy with precise weather data and accuracy of 86.4% ± 1.2% with satellite weather data, this method can identify defects with a severity as low as 5%, however this method has certain limitations, cannot precisely identify the exact faulty panels, and they may fail to detect faults that do not immediately affect the output power. Some of these undetected faults can lead to severe damage if they are not discovered and addressed at an early stage.

2.1. SOLAR CELL PHYSICS

2.1.1. P-N Junction Revisited

A p-type semiconductor, created by doping silicon with acceptor impurities such as boron which has holes as majority carriers and electrons as minority carriers. Conversely, n-type semiconductor, doped with donor impurities like phosphorus that has electrons as majority carriers and holes as minority carriers. When p-type and n-type materials merge, a depletion region forms where electrons from the n-side combine with holes from the p-side, resulting in a zone devoid of free charge carriers. This recombination process leaves positively charged donor ions in the n-region and negatively charged acceptor ions in the p-region. The width of the depletion region varies with doping levels, with higher concentrations leading to a narrower region. A built-in electric field arises due to the separation of these charged ions in the depletion region, creating a potential barrier that prevents the movement of majority carriers across the junction, thus maintaining equilibrium [57].

2.1.2. Behavior Under Illumination (Solar Cells)

When a solar cell is illuminated, photons with energy higher than semiconductor's bandgap excite electrons from the valence band to the conduction band, forming electron-hole pairs. The built-in electric field in the depletion region separates these pairs, driving electrons towards n-side and holes towards p-side. When connected to an external circuit, the separated electrons and holes flow, generating electric current. Current-Voltage (IV) characteristics of p-n junction under illumination show a shift, indicating photocurrent generation. Recombination, occurring both in depletion region and in bulk of p-type and n-type materials, impacts solar cell's efficiency. The diffusion length, which is the average distance minority carriers travel before recombining, is crucial; longer diffusion lengths are preferred for higher efficiency. Surface recombination, where carriers recombine at the semiconductor surface can reduce performance, but surface passivation techniques help mitigate this. Quantum efficiency the ratio of collected carriers to incident photons of a given energy, signifies effective carrier collection, with higher quantum efficiency indicating better performance [58].

2.1.3. Derivation of the Single-Diode Model

The behavior of solar cells is represented mathematically by a single diode model. The optical and recombination losses at the surface of the p-n junction are represented by a diode (D) a shunt resistance (R□□) is used to account for leakage currents, and a series resistance (R_s) is used to account for resistive losses in the model. The light generated current(I_{ph})is represented by the current source [59]. Here's the derivation:

The total current flowing through the external circuit is the light-generated current minus the diode current and the current through the shunt resistance as shown in equation (2.1).

$$I = I_{ph} - I_D - I_{sh} \tag{2.1}$$

Where:

I is the output current. I_{ph} is the photogenerated current. I_D is the diode current. I_{sh} is the shunt current.

Diode Current is represented in equation (2.2).

$$I_D = I_0\left(e^{\frac{V+IR_s}{nV_t}} - 1\right) \tag{2.2}$$

Where: I_0 is the diode saturation current. V is the voltage across the solar cell. Rs is the series resistance. n is the ideality factor. V_t is the thermal voltage which depicts in equation (2.3).

$$V_t = \frac{KT}{q}$$

(2.3)

Shunt Current is represented in equation (2.4).

$$I_{sh} = \frac{V+IR_s}{R_{sh}}$$

(2.4)

Where R_{sh} is the shunt resistance.

Combining these equations gives the single-diode model equation (2.5).

$$I = I_{ph} - I^0\left(e^{\frac{V+IR_s}{nV_t}} - 1\right) - \frac{\mathrm{V+IR_s}}{\mathrm{R_{sh}}}$$

(2.5)

2.1.4. Industrial Parameters

Key parameters in the single-diode model and their industrial relevance:

1. Short-circuit current (Isc) is the current when the voltage across the solar cell is zero (V=0). This is the maximum current the cell can provide.

2. Open-circuit voltage (Voc) is the voltage when the current through the solar cell is zero (I=0). This is the maximum voltage the cell can provide.
3. Maximum Power Point (MPP) is the point on the I-V curve where the product $I \times V$ is maximum. This is where the solar cell operates most efficiently.
4. Fill Factor (FF) is represented in equation (2.6). It is the ratio of the maximum power from the solar cell to the product of Isc and Voc.

   $$\text{FF} = \frac{I_{MP}.V_{MP}}{Isc.Voc} \tag{2.6}$$

   Efficiency (η) is the ratio of power output to solar power input as shown in equation (2.7).

   $$\eta = \frac{Pout}{Pin} = \frac{I_{MP}.V_{MP}}{Isc.Voc} \tag{2.7}$$

5. Series Resistance (R□) represents the resistive losses in the solar cell due to current movement through the cell material and contacts. Lower (R□) is desirable for higher efficiency.
6. Shunt Resistance (R□□) represents the leakage paths within the solar cell. High (R□□) is preferable as it indicates minimal leakage.
7. Photogenerated Current (I□□) depends on the incident light and cell temperature. Higher irradiance increases I□□
8. Saturation Current (I_O) is small current flows through the diode in reverse bias. It’s influenced by material properties and temperature.
9. Ideality Factor (n) indicates the deviation from the ideal p-n junction behavior. Typically ranges from 1 to 2.
10. Thermal Voltage (V□) is given by $Vt = \frac{KT}{q}$ where (K) is the Boltzmann constant, (T) is the temperature and (q) is the charge of an electron.

Designing and optimizing solar cells requires thorough understanding of their physics, especially as it relates to the p-n junction. With its associated characteristics the single-diode model offers a solid foundation for evaluating and enhancing solar cell performance. This model is crucial for guiding the development of more economical and efficient solar technology which is important for both academic research and industrial applications [60].

2.2. CONTEMPORARY SOLAR CELL TECHNOLOGIES

2.2.1 First-Generation Solar Cells

Rough estimates place the percentage of solar cells generated now using crystalline silicon wafers (c-Si) at close to 90% [61].

Silicon Solar Cells in Monocrystalline Form, these cells are composed of a single, continuous crystal structure and are well-known for their high efficiency (15–24%) and lengthy longevity. These cells are now less expensive than they were previously thanks to manufacturing advancements that have lowered the costs. They are widely used in both residential and commercial installations due to their excellent efficiency. Multi-Crystalline Silicon Solar Cells, also referred to as polycrystalline cells, these solar cells are created by melting many silicon crystals together. They are preferable for large-scale installations despite their lower efficiency (10–18%). They have low cost and a distinct blue, speckled appearance [62].

2.2.2 Second-Generation Solar Cells

Thin-Film Solar Cells: Thin film solar cells: These solar cells are fabricated by covering a substrate with very thin layers of PV material. Amorphous silicon (a-Si), Cadmium telluride (CdTe) and copper indium gallium selenide (CIGS) are some of the types. lightweight and flexible but they usually have a lower efficiency 13.6%,18.6 and 19.2% respectively and they need more space [63]

2.2.3 Third-Generation Solar Cells

Emerging Technologies: This category includes innovative designs like dye-sensitized solar cells (DSSCs), quantum dot solar cells, perovskite solar cells, and organic photovoltaics (OPVs). Perovskite cells have shown significant efficiency improvements over 25% in labs. These technologies focus on higher efficiency and lower production costs using abundant non-toxic materials and simpler processes.

Although still under development they hold the potential to revolutionize the solar industry with their efficiency, flexibility and cost effectiveness [64].

2.3. COMPARATIVE EVALUATION OF FAULT DETECTION APPROACHES IN SOLAR PV SYSTEMS

Fault detection is essential for maintaining efficiency and longevity of solar PV systems. Below is an assessment of various fault identification techniques.

2.3.1 Model-Based Approaches

These methods use mathematical models to predict the expected behavior of the PV system. Discrepancies between predicted behavior and real behavior indicate a fault. This method has high accuracy in detecting faults such as shading, soiling, and component degradation and provides detailed insights into the nature and location of faults. can also predict future faults using degradation models; however, this requires precise and sophisticated system modeling and may not adapt well to varying conditions without reconfiguration. Greater initial costs due to the need for accurate models and sophisticated software [65].

2.3.2 Signal-Based Approaches

Electrical signals, including voltage, current, and power output, are monitored using these techniques. These signals exhibit anomalies that could be defects. This technique offers real-time fault detection and is rather easy to deploy, can identify errors as they happen, enabling prompt intervention and lowering implementation and operating costs. But it has limitations for differentiating between fault types. Subject to false positives in a range of circumstances. Mostly useful for electrical faults, less so for mechanical faults or environmental effects [66].

2.3.3 Data-Driven Approaches

Use ML and statistical methods to analyze old and real-time data, learning fault patterns from large datasets. Highly adaptable to various PV systems and conditions. Capability to handle large datasets and complex systems, high precision in identifying and diagnosing faults. The drawback is that they need large amounts of high-quality data for training, high computational power is required for processing and analysis and generalizability concerns due to the risk of overfitting the model to training data [67].

2.3.4 Hybrid Approaches

Integrate elements of model-based, signal-based and data-driven methods to exploit the effectiveness of each. This approach boosts robustness and accuracy by integrating several detection techniques. More resilient to varying conditions and system alterations. Provides detailed fault diagnosis while maintaining real-time detection. However, there is complexity in implementation, increased needs for data management and processing capacity and difficulties combining different methods for perfect performance [68].

Model-Based Approaches are complex and sensitive to changes in the environment, but they provide high accuracy and thorough diagnostics.
Signal-Based Approaches are simple, affordable, and capable of real-time detection, however, have limitations in terms of fault distinction and are prone to false positives.
Data-Driven Approaches are extremely accurate and adaptive, needing large amounts of data and processing power, deep learning increases efficacy.
Hybrid Approaches are powered by AI and IoT and offer comprehensive and resilient defect detection, are resource- and complexity-intensive.
There are advantages and disadvantages to each strategy. The decision is made considering the PV system's particular requirements and limitations, which include resource availability, environmental factors, and accuracy standards.

2.4. TRADITIONAL METHODS VS AI TECHNIQUES

Traditionally, fault detection in solar PV systems has relied on manual inspection, visual assessment or simple rule-based algorithms. While these methods can identify apparent faults, they often struggle to detect subtle anomalies or predict impending failures. In contrast AI-based approaches offer the potential to analyze vast amounts of data collected from PV systems uncover hidden patterns and provide early warnings for potential faults These advanced techniques have the adaptability and scalability to revolutionize the industry of solar PV [69,70].

One of the fundamental aspects of utilizing AI for fault detection in solar PV panels is the availability of high-quality data. A lot of studies focused on collecting, preprocessing and analyzing data from various sensors embedded within PV systems including voltage and current sensors temperature sensors, irradiance sensors and so on. By leveraging this data researchers have developed sophisticated models capable of identifying different types of faults such as degradation, soiling, shading and electrical mismatches with high accuracy [71–73].

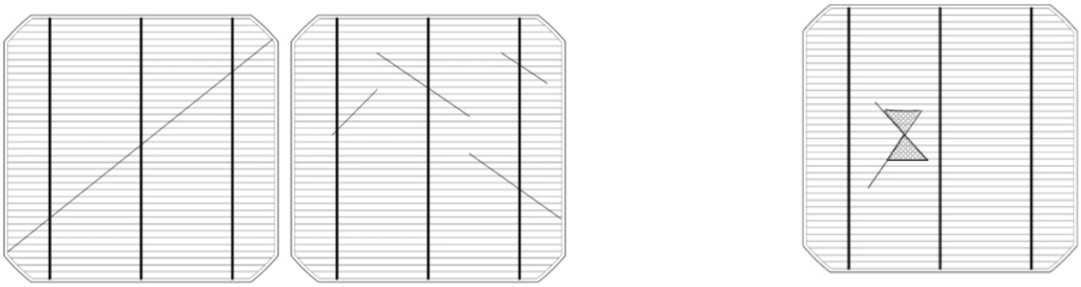
Although deep learning models excel in fault detection, they typically demand significant computational resources for training and inference, which restricts their scalability and practical use in resource-limited environments. Consequently, a balance between model complexity and computational efficiency must be thoughtfully considered in system design.

Despite their high accuracy the black-box nature of certain AI models, particularly deep neural networks, pose challenges in interpreting and explaining their decisions. Addressing this issue is critical for facilitating the adoption of AI-driven fault detection systems in the solar industry.

2.5. IMPACT OF CRACKS ON SOLAR CELL PERFORMANCE

Cracks in solar cells can impede current flow, thereby lowering output power of solar PV systems. The main concern with cracks is that they can create failures, which reduce the power output[74]. For instance, as shown in Figure 2.1. (a), an undetected crack has no effect, so the influence on output power remains minimal. However,

Figure 2.1. (b) depicts cracks in solar cells that affect output power of solar PV systems.



(a) (b)

Figure 2.1. Linear cracks (b) severe cracks [75].

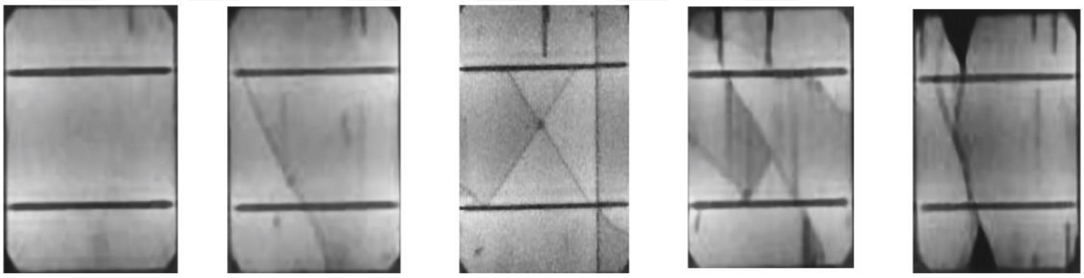


Figure 2.2. Healthy to Unhealthy PV Panels [75].

Additionally, Figure 2.2. exhibits the five cracks' categories in PV panel, ranked from least to most severe regarding their impact on solar PV panel's output power. The classification ranges from "normal" to "broken", highlighting the varying degrees of damage. The rapid detection and rectification of faults is crucial for preserving efficiency and optimizing energy output in huge PV plants, where this enhancement could be extremely beneficial.

This thesis assesses artificial intelligence (AI) techniques according to how well they can identify faulty modules in solar PV plants to ensure reliability and efficiency of solar PV system. AI like CNN, PSO, ACO, SVM, DT, KNN, ensemble, and discriminant were utilized to find indicative features and classify faulty solar PV panels.

PART 3

METHODOLOGY

We employ CNNs based on encoder to extract features from EL images of defective and non-defective panels, then use metaheuristic approaches such as PSO and ACO for the selection of the best features that are most indicative of faults to lower the model's computational complexity and time and improve accuracy and reliability.
The rationale for choosing CNNs lies in their superior performance in image classification tasks, while ACO and PSO were selected for their effectiveness in feature selection and optimization. To enhance understanding, pseudocode and flowcharts for the proposed algorithms are included. The CNN model is illustrated in Figure 3.1, showing the architecture used for fault detection. Additionally, the feature selection process using ACO and PSO is depicted in Figure 3.2, outlining the steps from data preprocessing to model evaluation.

The architectute of CNN model that used in this thesis is illustrated in figure 3.1.

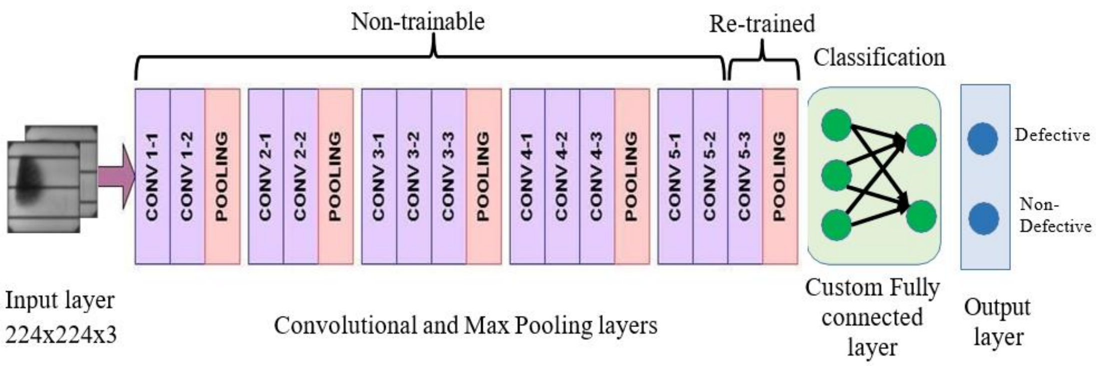


Figure 3.1. The CNN Model [76]

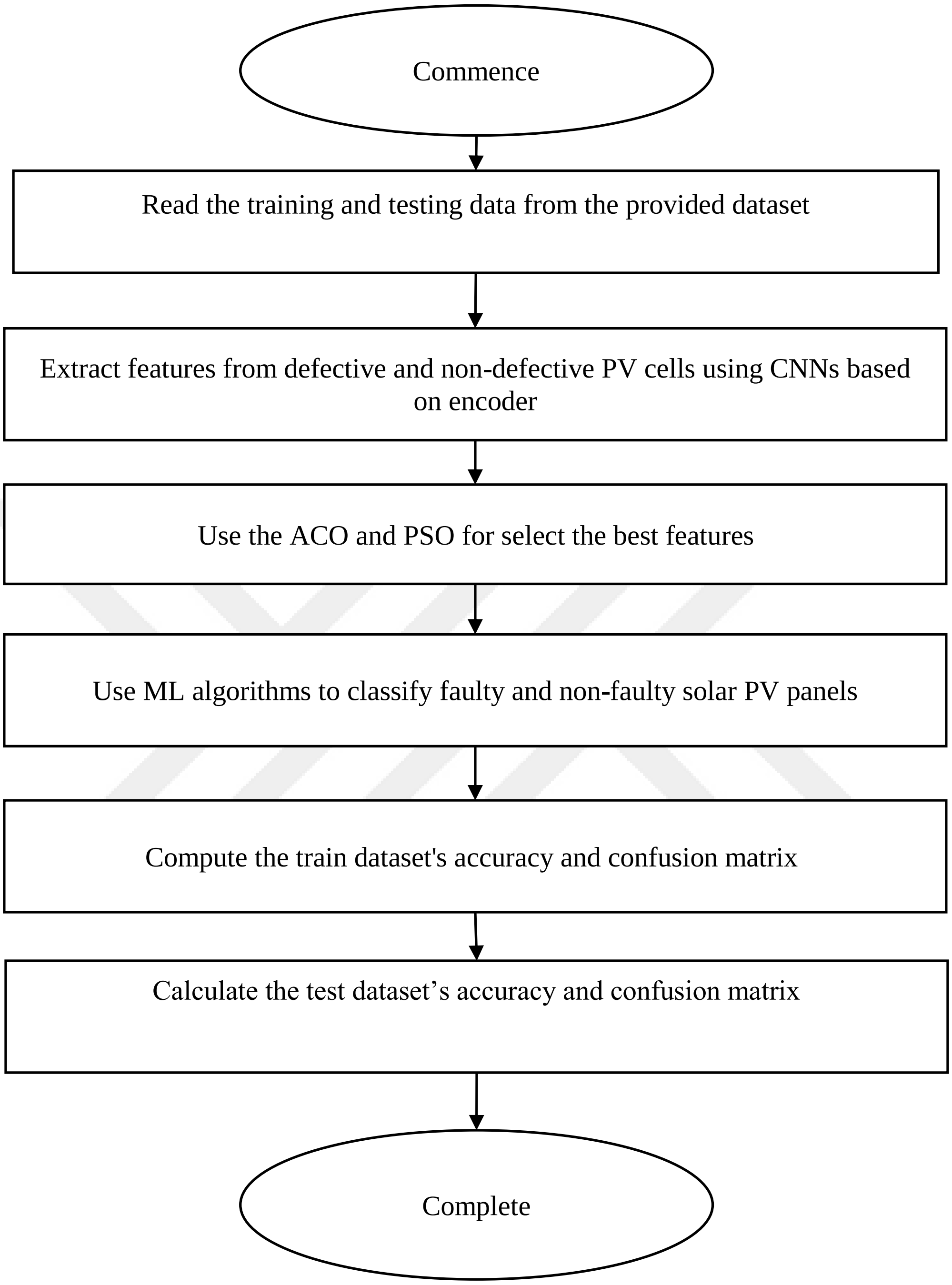


Figure 3.2. Steps of the proposed method

3.1. MODEL TRAINING AND EVALUATION

Divide the dataset into subsets 70% for training and 30 % for testing to train and evaluate the models' performance.

To maximize model performance fine-tune hyperparameters using randomized search techniques.
Use performance metrics to assess the models for detecting malfunctioning solar panels such as recall, precision, F1-score and accuracy.

3.2. PARTICLE SWARM OPTIMIZATION (PSO)

The computational optimization method known as PSO is modeled after the social behavior of living things, including fish schools and flocks of birds. Kennedy and Eberhart first suggested it in 1995. PSO models the behavior of a swarm of particles moving over a multidimensional search space to find the optimal solution to a given optimization problem [77].

3.2.1. Formulation of Equations for PSO

The following steps show the mathematical formulation of PSO:

1. Initialization:
   Assign random starting points and velocities to all the particles in the search space.
   Every particle's position serves as a possible solution to the optimization issue, and its velocity dictates the direction and speed of its motion.

2. Update Particle Velocity:
   Every particle's velocity is updated based on its distance from its best-known position (personal best) its current velocity and the distance from the best-known position of the swarm (global best).
   The velocity update of particle is represented in equation (3.1).
   $$v_{i,d}^{t+1} = w \cdot v_{i,d}^{t} + c_1 \cdot r_1 \cdot \left(p_{i,d} - x_{i,d}^{t}\right) + c_2 \cdot r_2 \cdot \left(p_{g,d} - x_{i,d}^{t}\right)$$
   (3.1)
   where:
   $v_{i,d}^{t+1}$ is updated velocity of particle i in dimension d at iteration t+1.
   w is the inertia weight.

c_1 and c_2 are the cognitive and social acceleration coefficients, respectively.

r_1 and r_2 are random numbers between 0 and 1.

$p_{i,d}$ is the personal best position of particle i in dimension d.

$p_{g,d}$ is the global best position found by any particle in dimension d.

$x_{i,d}^{t}$ is the current position of particle i in dimension d at iteration t.

3. Update Particle Position:

   The position of each particle is updated based on its current position and velocity.

   The position update of particle is represented in equation (3.2).

   $$x_{i,d}^{t+1} = x_{i,d}^{t} + v_{i,d}^{t+1}$$

   (3.2)

   where:

   $x_{i,d}^{t+1}$ is the updated position of particle i in dimension d at iteration t+1.

   $v_{i,d}^{t+1}$ is the updated velocity of particle i in dimension d at iteration t+1.

   $x_{i,d}^{t}$ is the current position of particle i in dimension d at iteration t.

4. Update Personal Best and Global Best:

   Update each particle's personal best position based on its fitness value.

   Update the global best position based on the best fitness value among all particles.

The algorithm based on the mathematical formulation is expressed in previous steps [77].

3.2.2. Pseudocode for PSO

```
BEGIN
  Randomly initialize particle locations and velocities
  FOR each particle
    Evaluate the fitness of the particle f(xi)
    IF f(xi) > gBest THEN
```

```
    Update gBest to f(x_i)
  ENDIF
  IF f(x_i) > pBest THEN
    Update pBest to f(x_i)
  ENDIF
 ENDFOR
 WHILE NOT exit criterion met DO
  FOR each particle
    Update particle velocity vector v_i
    Update particle position vector x_i      Evaluate the fitness of the particle f(x_i)
    IF f(x_i) > gBest THEN
      Update gBest to f(x_i)
    ENDIF
    IF f(x_i) > pBest THEN
      Update pBest to f(x_i)
    ENDIF
  ENDFOR
 ENDWHILE
 OUTPUT the best solution found (gBest) and its fitness value
END
```

3.2.3. Flowchart for PSO

The flowchart for PSO figure 3.3. outlines the key steps, illustrating how particles move through the solution space to find optimal solutions.

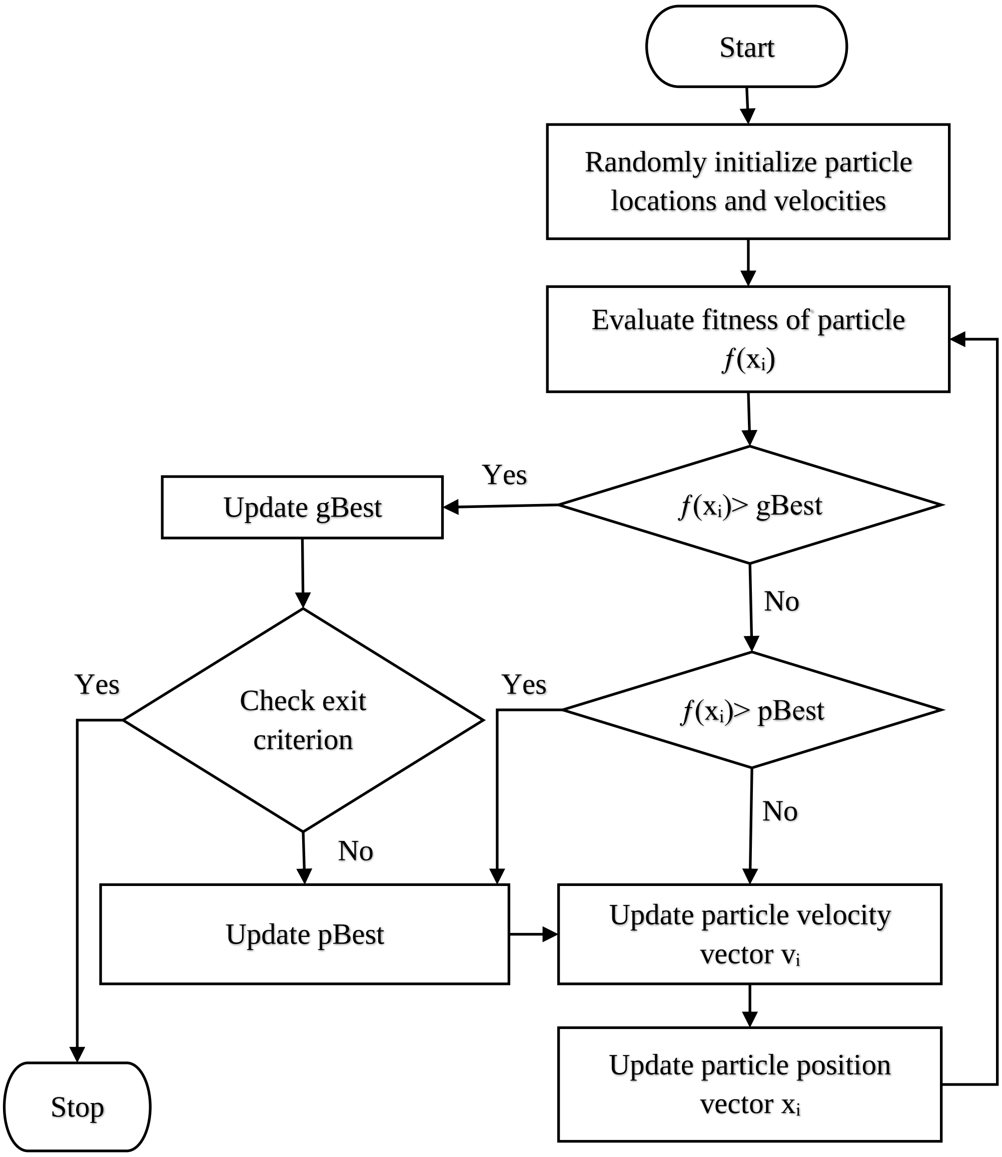


Figure 3. 3. Flowchart for PSO

3.3. ANT COLONY OPTIMIZATION (ACO)

Ant Colony Optimization (ACO) introduces a novel concept that optimizes a range of methods based on natural mechanisms and codes of conduct observed in ant colonies. ACO is formed by emulating the behavior of ants in their real-life exploratory search for food. Notably, the algorithm leverages a direct chemical communication mechanism called pheromones. The small ants have the remarkable ability to determine the quickest route between two locations. Initially, an ant explores the surroundings randomly in search of food. During this exploration, the ant drops a chemical trail known pheromones through a certain path. The purpose of pheromones is to guide other ants towards the target point. The amount of pheromones present on a given route influences the choice made by subsequent ants. Many factors affect the quantity of pheromones that an ant leaves behind, including the amount of food discovered, the number of ants present, and the frequency of ants passing through that particular area. [78].

Figure 3.3 illustrates an example of the movement mechanism employed by ants to reach food by following the track of pheromones. When encountering an obstacle, all ants have an equal probability of choosing the upward path as it is shorter than the downward path. Consequently, the upward pathway accumulates higher levels of pheromones.

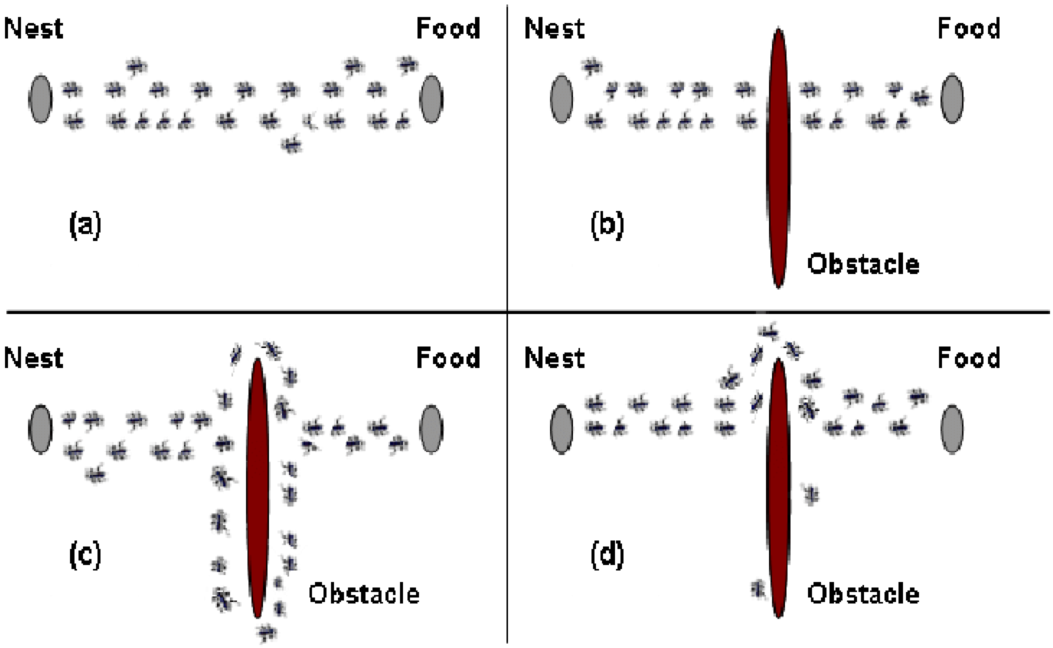


Figure 3.4. Depicts the movement mechanism of Ants when faced with obstacles. Ants in a real colony having an equal chance of turning left or right; (a) They travel a route from their nest to the location of food.; (b) they deposit more pheromone on the shorter route; and (d) most ants have selected the shortest way [79].

3.3.1. Formulation of Equations for ACO

The algorithm based on the mathematical formulation is shown in following steps [78].

1. Problem Representation:
   Fault detection in solar PV panels using ACO
   Consider a graph G = (N, E) where N is the set of nodes and E is the set of edges connecting the nodes. The aim is to find the optimal solution.

2. Pheromone representation:
   τ_{ij}(t) represent the pheromone level on edge (i , j) at time t.

3. Heuristic Information:

η_{ij} is the heuristic information associated with edge (i , j) this usually the inverse of distance or cost associated with the edge as shown in equation (3.3).

$$\eta_{ij} = \frac{1}{d_{ij}} \quad (3.3)$$

where $d_{ij}$is the distance or cost between nodes i and j

4. Probabilistic Transition Rule:

The probability $P_{ij}^{k}(t)$ of ant k moving from node i to node j at time t is given by equation (3.4).

$$P_{ij}^{k}(t) = \frac{[\tau_{ij}(\mathrm{t})]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{l \in N_k}[\tau_{ij}(\mathrm{t})]^{\alpha}[\eta_{ij}]^{\beta}} \quad (3.4)$$

Where α is the parameter controlling the influence of pheromone.

β is the parameter controlling the influence of heuristic information.

Nk is the set of nodes that ant k can visit from node i.

5. Pheromone Update:

The pheromone update involves two steps: pheromone evaporation and pheromone deposition.

Pheromone Evaporation is expressed in equation (3.5)

$$\tau_{ij}(t+i) = (1-\rho)\,\tau_{ij}(\mathrm{t})$$

(3.5)

where ρ is the evaporation rate ($0 < \rho > 1$)

Pheromone Deposition is represented in equation (3.6).

$$\tau_{ij}(t+i) = \tau_{ij}(t+i) + \Delta\tau_{ij} \quad (3.6)$$

Where $\Delta\tau_{ij}$ is the amount of pheromone deposited by all ants, as it is depicted in equation (3.7).

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta{\tau_{ij}}^{k} \quad (3.7)$$

And $\Delta{\tau_{ij}}^{k}$ is the pheromone deposited by ant k.

6. Solution Construction:

Each ant gradually constructs a solution by applying probabilistic transition rule until a complete solution is formed.

7. Stopping Criterion:
The algorithm iterates through solution formation and pheromone update until the stopping criterion is met.

3.3.2. Pseudocode for ACO

```
BEGIN
  Set values for ACO parameters
  Generate initial regions and evaluate the objective function
  Initialize the pheromone concentration for each region
  While stopping condition not met:
    FOR each ant DO
      Construct a solution based on pheromone levels and heuristic information
      Evaluate the objective function of the constructed solution
    END FOR
    Update pheromone levels based on the quality of the solutions
    Apply pheromone evaporation process
  END WHILE
  Perform local optimization on the best solution found
  OUTPUT the best solution and its objective function value
END
```

3.3.3. Flowchart for ACO

The flowchart for ACO figure 3.5. describes the main steps, which shows how ants navigate the searching space in search of the optimal solution.

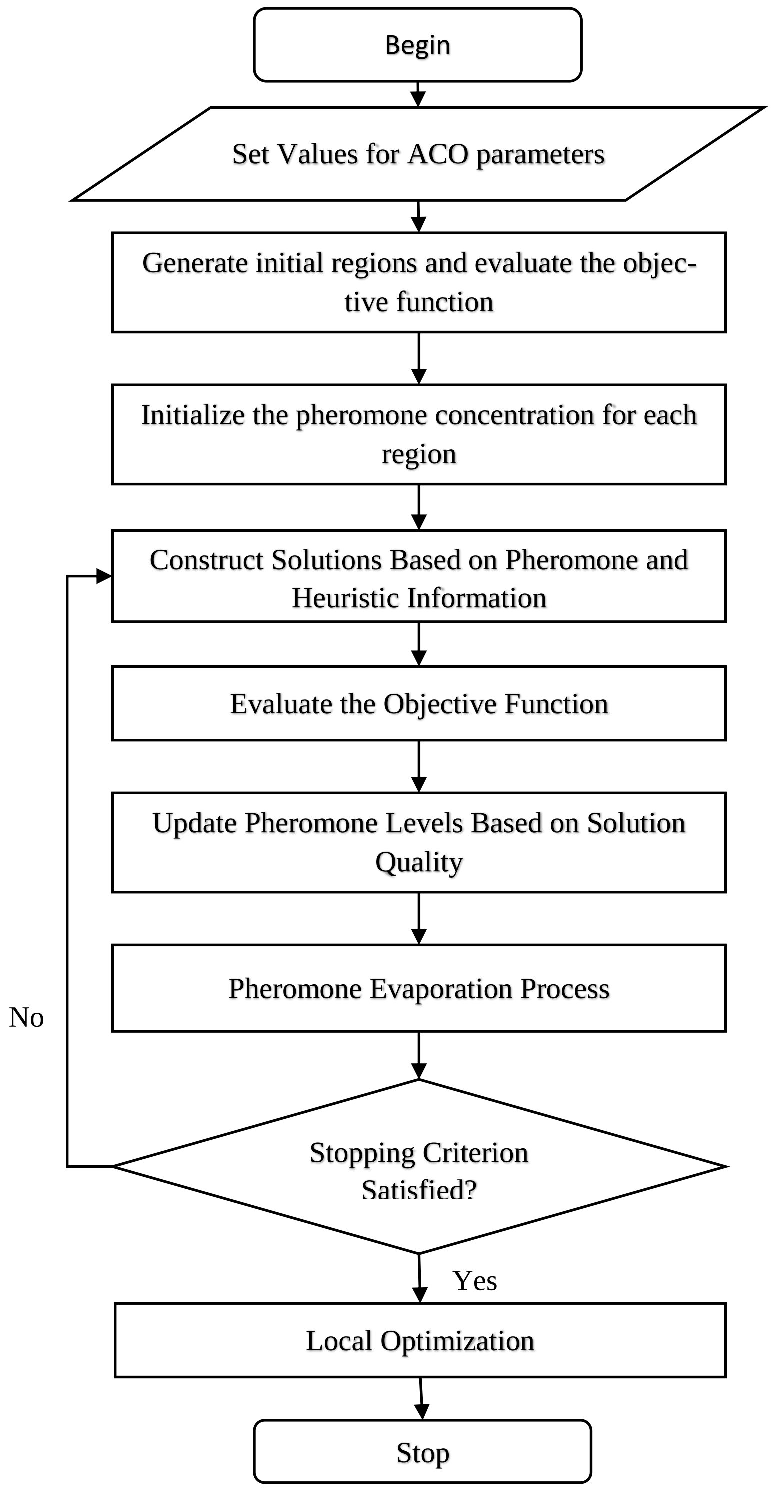


Figure 3.5. Flowchart for ACO

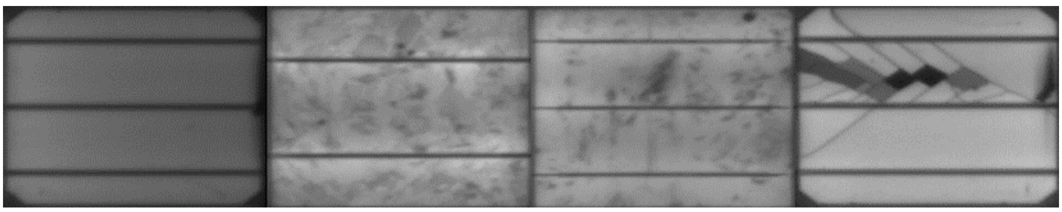
3.4. DESCRIPTION OF DATASET

The methodology section details the dataset used, which comprises of 2624 grayscale PV images sourced from 44 distinct solar modules. Each image is preprocessed for perspective and size to eliminate lens distortion. Each image measuring 300*300 pixels. 8-bit depict defective and non-defective PV panels, each image is preprocessed for perspective and size to eliminate lens distortion, autoencoder was utlizied to reduce the dimentionality of data by learning compressed representations (latent space) and removing noise from data by learning the underlying patterns.

The dataset samples are a combination of both monocrystalline and polycrystalline solar cells (1074 monocrystalline images and 1550 polycrystalline images). The observed defects fall into two categories: internal or external, both negatively impacting the performance of solar PV systems.GitHub is the source of the dataset [80].

3.5. DATA ANALYSIS

Specialists examined the images and assigned labels representing the likelihood of a defect. These labels correspond to four classes associated with a specific likelihood of a malfunction: 0.0, 0.33, 0.66, or 1.0. A defect probability of 0.0 signifies a perfectly healthy cell, as shown in Figure 3.6. (a). Figure 3.6. (b) indicates a cell with minor defects (probability 0.33), Figure 3.6. (c) depicts a cell with moderate defects (probability 0.66), and Figure 3.6. (d) shows a cell with severe defects (probability 1.0). The defect probability value serves as an indicator of the severity of defects present in the photovoltaic (PV) cell.



(a) (b) (c) (d)

Figure 3.6. Samples of Defective Probability of PV Modules

The table 3.1. shows that the dataset is split into two classes: one that is non-faulty and is formed by combining the probability of 0 and 0.33, and another that is faulty and is formed by combining the probabilities of 0.66 and 1.

Table 3.1. Information of dataset

State	Defective likelihood	Images per samples
Non-Faulty	0% faulty	1508
	33% faulty	295
Faulty	% 66 faulty	106
	% 100 faulty	715
Total	2624	

3.6. PARAMETERS OF ACO

The table 3.2. represents the used parameter for ACO to optimize the selection of features of faulty and non-faulty solar PV panels.

Table 3.2. Parameters for ACO

Parameter	Value
Number of ants (N)	100
Maximum iterations (max._Iter.)	50
Initial tau (τ)	0.3
Initial eta (η)	0.5
Coefficient controlling tau (α)	0.8
Coefficient controlling eta (β)	0.3
Pheromone evaporation rate (ρ)	0.2
Validation set percentage (ho)	20%

3.7. PARAMETERS OF PSO

The table 3.2. represents the used parameter for PSO to optimize the selection of features of faulty and non-faulty solar PV panels.

Table 3.3. Parameters for PSO

Parameter	**Value**
Number of particles (N)	100
Maximum iterations (T)	50
Cognitive factor (C1)	2
Social factor (C2)	2
Maximum velocity (Vmax)	6
Maximum bound on inertia weight (Wmax.)	0.9
Minimum bound on inertia weight (Wmin.)	0.4

3.8. PERFORMANCE EVALUATION OF AI MODELS

We assessed the effectiveness of our suggested approach by employing common evaluation metrics, including accuracy, sensitivity, precision and F1. The requirements for each of the indicators are as follows equations (3.8), (3.9), (3.10) and (3.11) respectively [81][82–85]:

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \times 100\%$$

(3.8)

$$Sensitivity\ (Recall) = \frac{TP}{TP+FN} \times 100\%$$

(3.9)

$$Precision = \frac{TP}{TP+FP} \times 100\%$$
(3.10)

$$F1 = 2 \times \frac{Recall \times precision}{Recall + precision} \times 100\%$$
(3.11)

Each of these indicators is determined using the False Positive (FP), True Negative (TN), False Positive (TP), and False Negative (FN).

The implementation environment for this thesis utilizes MATLAB R2022b and an Intel Core I5 with 4.82 GHz CPU

3.9. IMPLEMENTATION AND DEPLOYMENT

To continuously monitor the performance of solar panels include the learned models into a real-time monitoring system with an intuitive user interface for the results' display and interpretation, the interface should include action recommendations and alarms for faults. The defect detection system should be deployed in experimental solar installations to evaluate its functionality in real-world scenarios. Over time track and assess the system's performance and making adjustments based on feed-back from field testing to increase precision and dependability.By following these materials and methods, this thesis aims to develop and validate effective AI tech-niques for the detection of faulty solar panels contributing to the enhancement of sustainable energy and the optimization of solar energy systems

Overall, our methods encompassed the integration of CNNs techniques with the ACO and PSO algorithms to develop a robust approach for faulty solar PV modules detection, leveraging the complementary strengths of both methodologies.

PART 4

RESULTS AND DISCUSSION

4.1 DISCUSSION OF KEY FINDINGS

The developed AI models show robust and accurate performance in detecting faulty solar PV panels. This highlights their generalizability and potential for widespread adoption in real-world solar systems.

In this work decision tree, discriminant, KNN, ensemble, and SVM were employed to categorize the faulty PV solar panels.

CNNs based on encoder extracted 100 features from the input data. When metaheuristic algorithms were applied, the number of features significantly decreased: PSO reduced the number of features from 100 to 53, and ACO reduced the number of features from 100 to 34. Despite the reduced numbers of features, the used classifiers were still able to predict faulty and non-faulty panels with impressive results for most of them.

4.2 PERFORMANCE EVALUATION

For evaluation the confusion matrix was used, and the results were as following:

4.2.1 Accuracy

The developed AI models achieved high accuracy rates in detecting faulty solar panels.

The results of decision tree, SVM, ensemble, KNN and discriminant were 94.88 %, 76.20%, 98.34, 97.45%, and 80.23, respectively.

4.2.2 Precision

Precision scores were consistently high, indicating the models' ability to accurately identify both faulty and non-faulty panels. Precision values for decision tree, SVM, ensemble, KNN and discriminant were 93.64%, 76.75%, 98.98%, 97.21% and 77.90% respectively, demonstrating robust performance in minimizing false positives and false negatives.

4.2.3 Sensitivity (Recall)

Recall results for decision tree, SVM, ensemble, KNN and discriminant were 93.42%, 57.93, 98.22%, 97.99% and 68.14% respectively.

4.2.4 F1-Score

F1-scores which balance precision and recall were 93.53% for decision tree, 66.02% for SVM, 97.25% for ensemble, 96.48% for KNN and 72.70 for discriminant, indicating high degree of overall performance in fault detection.

4.3 RESULTS OF CNN BASED ON THE ENCODER

Figure 4. 1 displays the results of recall, accuracy, precision, and F1 Score. Ensemble approach yielded the best results in this investigation; the percentages of accuracy, precision, recall, and F1 Score were 98.34%, 98.98%, 98.22%, and 97.25%, respectively. SVM approach yielded the lowest accuracy and performance, with accuracy, precision, recall, and F1 Score being 76.20%, 76.75%, 57.93%, and 66.02%, respectively.

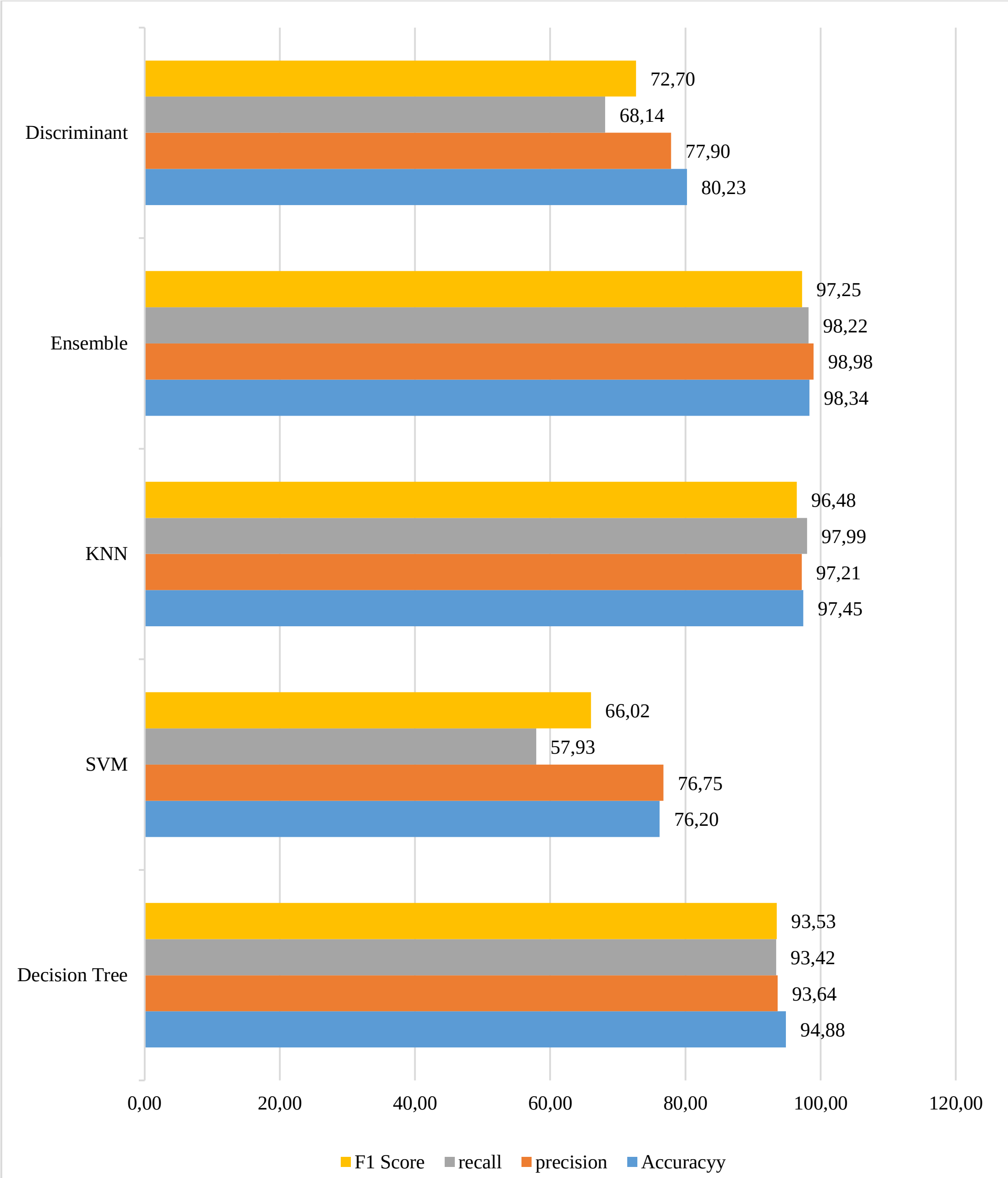


Figure 4.1. Findings for F1 Score, recall, accuracy, and precision

4.4 RESULTS BASED ON ANT COLONY OPTIMIZATION (ACO)

Recall, accuracy, precision and F1 Score findings are shown in Figure 4. 2. The best findings were obtained by ensemble, the corresponding percentages for accuracy, precision, recall and F1 Score were 97.90%, 97.62%, 97.34% and 97.30%, respectively. The lowest results were produced by SVM, accuracy, precision, recall and F1

Score were 83.57%, 78.20%, 70.46% and 75.96%, respectively. These results were acquired after reducing the number of features from 100 to 34 by ACO.
The results based on the ACO is shown in figure 4.2.

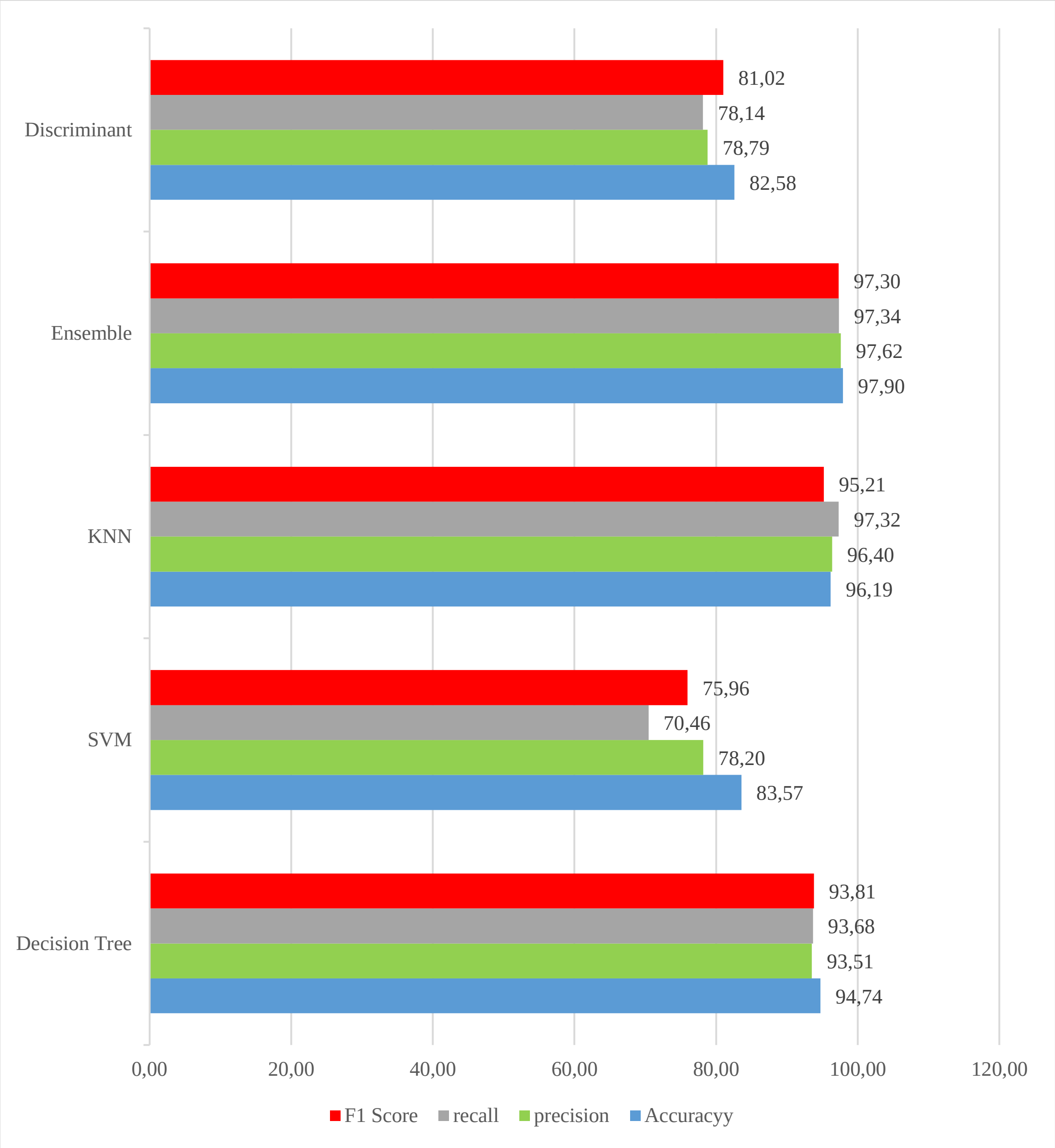


Figure 4. 2. Results based on ACO

4.5 RESULTS BASED ON PARTICLE SWARM OPTIMIZATION (PSO)

Figure 4.3 displays recall, accuracy, precision, and F1 Score results. Ensemble approach yielded the best results from the experiment; the corresponding percentages for recall, accuracy, precision, and F1 Score were 96.67%, 96.34%, 96.25%, and 96.99%, respectively. For SVM, the corresponding values were 83.08%, 79%, 70.02%, and 75.04% for accuracy, precision, recall, and F1 Score. The least accurate and performing method was this one. These outcomes were obtained following PSO's reduction of the feature count from 100 to 53.

The results based on the PSO is shown in figure 4.3.

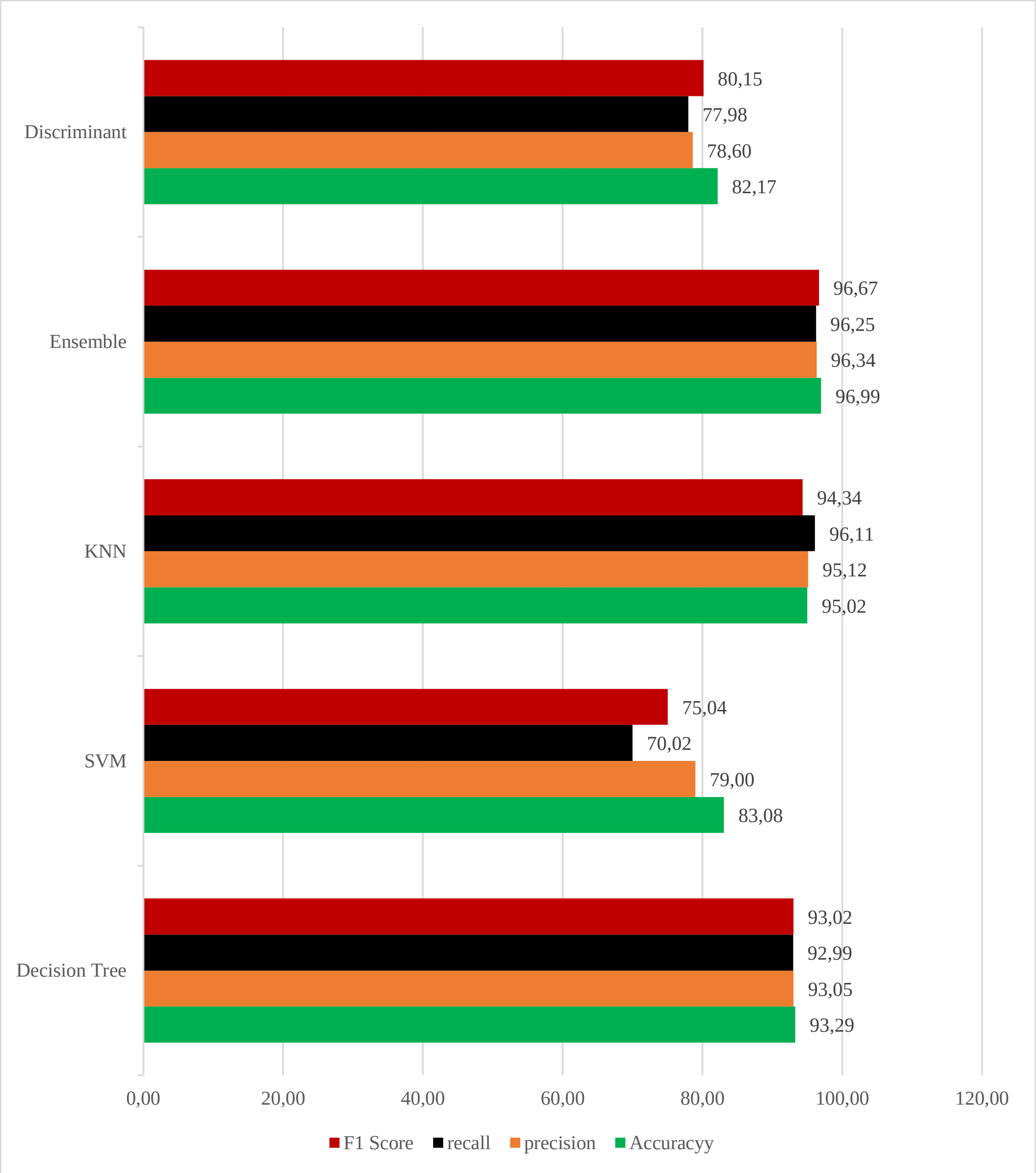


Figure 4.3. Results based on PSO

4.6 COMPARATIVE ANALYSIS WITH EXISTING STUDIES

The comparison of our results with previous works demonstrates that the obtained results surpass those mentioned in the literature review. For instance, the study [43] proposed deep learning methods for identifying faults in PV systems, the suggested approach employed LIRNet and LWCNN achieving an accuracy rate of 89.1%, in contrast, our method shows high accuracy in detecting faulty solar PV panels.

The study [44] presented an approach using string measurement data to categorize defects in PV plants. Drones equipped with thermographic cameras were used to identify faults and the results were cross-checked with string measurement data, resulting in an accuracy rate of 74.0%, which is significantly lower compared to the results obtained from our AI models. Additionally, the study [46] proposed an automated method for locating faults in PV arrays using artificial intelligence, using a dataset of 2,624 solar cell images, the VGG feature descriptor was found to be the most effective, with KAZE/VGG identified as the top-performing classifier. CNN exhibited superior performance compared to the SVM, achieving an average accuracy of 88.42%, while the SVM achieved 82.44%, the obtained results by this method prove that our suggested approach is much better. The framework presented in [47] employed Electroluminescence (EL) imaging for detecting faults in PV solar systems using a dataset of mono- and polycrystalline PV images. This framework uses an isolated deep learning approach with a six-layer CNN architecture, achieving 93% accuracy with a standard deviation of 0.37%, which is still less than the achieved accuracy by our model.

The study in [48] proposes a CNN model for classifying and detecting defective solar PV panels using electroluminescence images. The dataset used in this research consists of 1,800 EL images illustrating four distinct module conditions. The findings show that the combined method of Generative Adversarial Networks (GAN) and traditional image processing achieved the best performance with an accuracy of 83%. Lastly, the method described in [49] focuses on generating physically relevant labels of defects and detecting them using a deep CNN in inline measurements of solar cells. The study utilized a dataset of approximately 6,800 mc-Si and high-performance mc-Si wafers from ten different manufacturers. The CNN achieved 88% precision, 91% recall for j_o faults, 78% precision and 86% recall for Rs faults.

By this comparison, we can prove that the suggested approach in this thesis exceeded previous works for the detection and classification of faulty solar PV panels.

PART 5

CONCLUSION AND FUTURE WORKS

5.1 CONCLUSION

The results presented in this thesis underscore the effectiveness and potential of AI techniques in accurately identifying faulty solar PV panels. By harnessing the power of advanced algorithms, we have demonstrated high levels of accuracy, precision and recall in fault detection paving the way for proactive maintenance strategies and optimized performance of solar PV system.

The comparative analysis of different AI approaches has offered insightful information about the strengths and limitations of various techniques highlighting the importance of selecting appropriate algorithms and feature engineering methods depending on the characteristics of the data and the desired performance metrics.

In conclusion the findings presented in this thesis help the development of renewable energy and underscore the transformative potential of AI in shaping the future of solar energy production. By fostering innovation, collaboration and interdisciplinary research we can continue to drive progress towards a more resilient, efficient and sustainable energy infrastructure for generations to come.

This thesis offers a technique for classifying defective PV panels Utilizing CNNs based on the encoder to extract features from images of defective and non-defective panels then using metaheuristic approaches such as PSO and ACO for the selection of best features that are most indicative of faults to lower the complexity and computational time and improve the accuracy and reliability of the model. After that, employ extracted features with different ML algorithms to classify faulty and non-faulty panels. The model is trained on a dataset consisting of four classes representing 0%, 33%, 66% and 100% defect rates. Various machine learning algorithms, including decision tree (DT), support vector machine (SVM), K nearest neighbor (KNN), ensemble and discriminant were applied, achieving accuracy rates of 94.88%, 76.20%, 97.45%, 98.34% and 80.23%, respectively.

Ensemble and KNN demonstrated competitive performance in fault detection, with ensemble exhibiting slightly higher accuracy. Ensemble approach yielded the best results in this investigation; the percentages of accuracy, precision, recall, and F1 Score were 98.34%, 98.98%, 98.22%, and 97.25%, respectively. KNN results were 97.45%, 97.21%, 97.99%, and 96.48%, respectively. SVM approach yielded the lowest accuracy and performance, with accuracy, precision, recall, and F1 Score being 76.20%, 76.75%, 57.93%, and 66.02%, respectively.

5.2 FUTURE WORKS

Integration of additional data sources such as thermal imaging, infrared thermography, and drone-based inspections with EL imaging to enhance fault detection accuracy and model robustness. Also investigate the use of hybrid optimization techniques combining ACO and PSO with other methods like genetic algorithms or simulated annealing for more efficient feature selection.

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RESUME

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