P E A R L P V

Fault detection for PV systems using machine learning techniques

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Training School III

Simulation tools and models for the analysis of PV system performance

Brasov, Romania,

07.07.2021

Overview

❖ Why do PV systems fail?

❖ Defects and Failures in PV modules, components and systems

❖ Failure detection techniques

❖ Why is intelligent fault diagnosis for PV system important?

❖ Artificial intelligence techniques

❖ Machine learning process for faults detection in PV systems

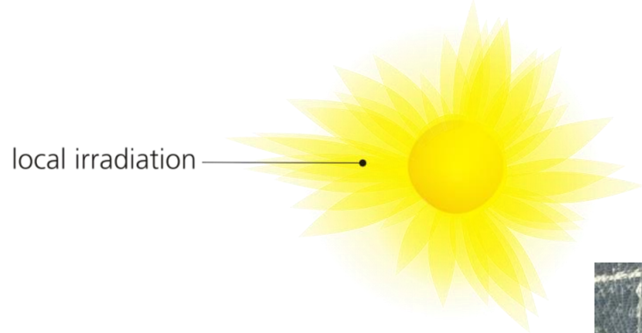
❖ Electrical faults (DC side) detection/classification in PV systems using machine learning techniques

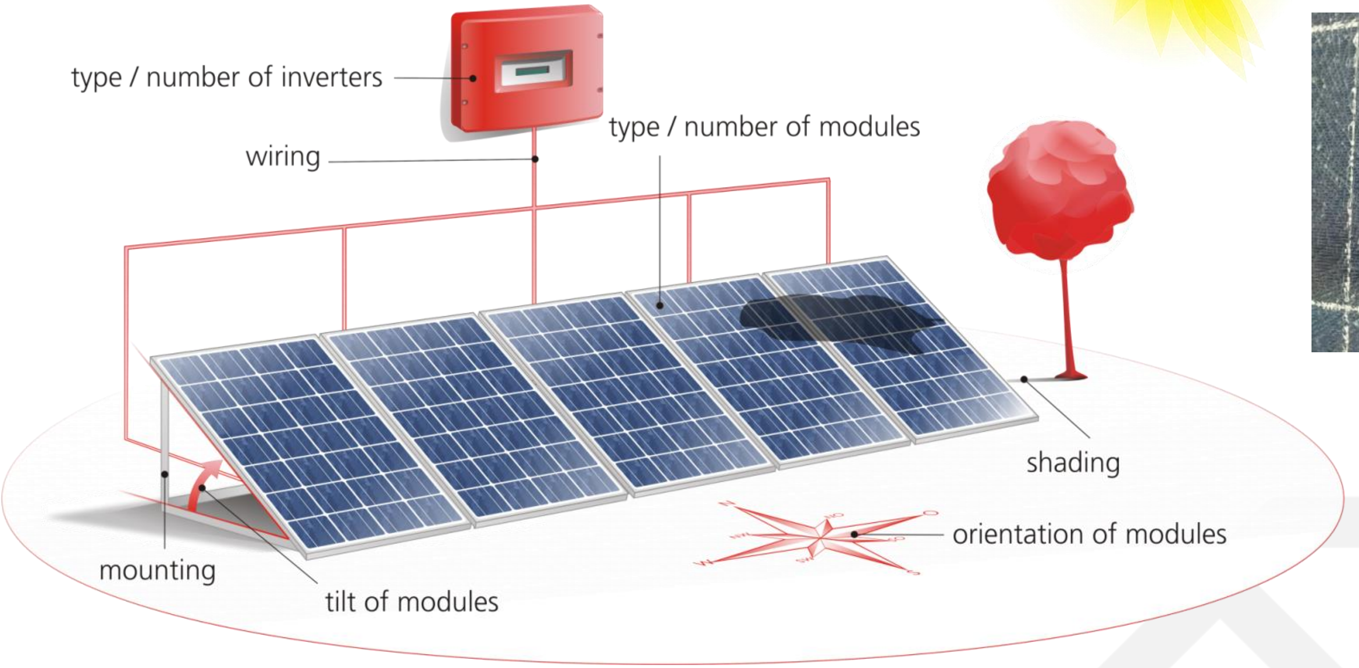
❖ Defects/failures (visible) detection in PV strings using fully convolutional network (FCN)

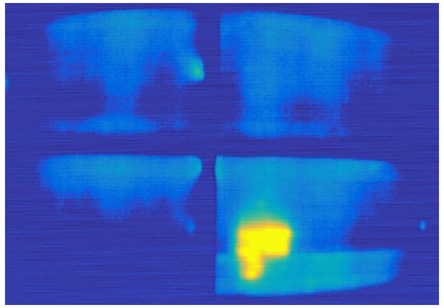
❖ Failures (IR) detection in PV strings using convolutional neural network (CNN)

❖ Failures (EL) detection in PV strings using generative adversarial network (GAN) and convolutional neural network (CNN)

Why do PV systems fail?

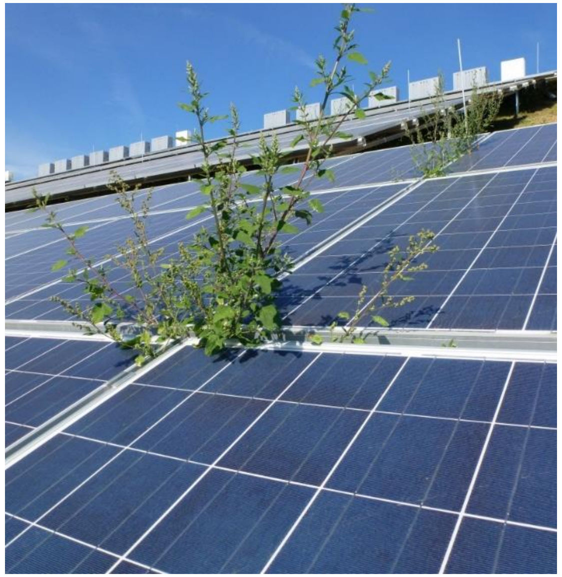


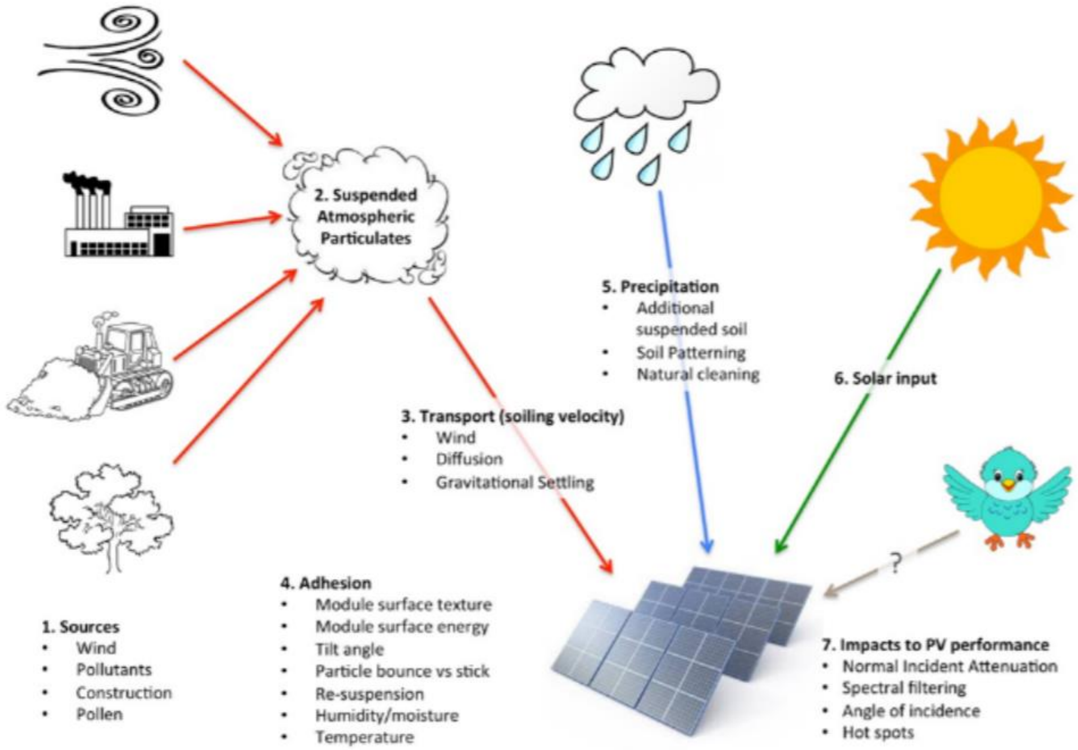




Fraunhofer ISE, Photovoltaics Division, Christian Schill
Prof. Ricardo Rüther – Fotovoltaica/UFSC
PV Performance Modeling Methods and Practices ,Results from the 4th PV Performance Modeling Collaborative Workshop, PVPS IEA, 2017.

Why do PV systems fail?

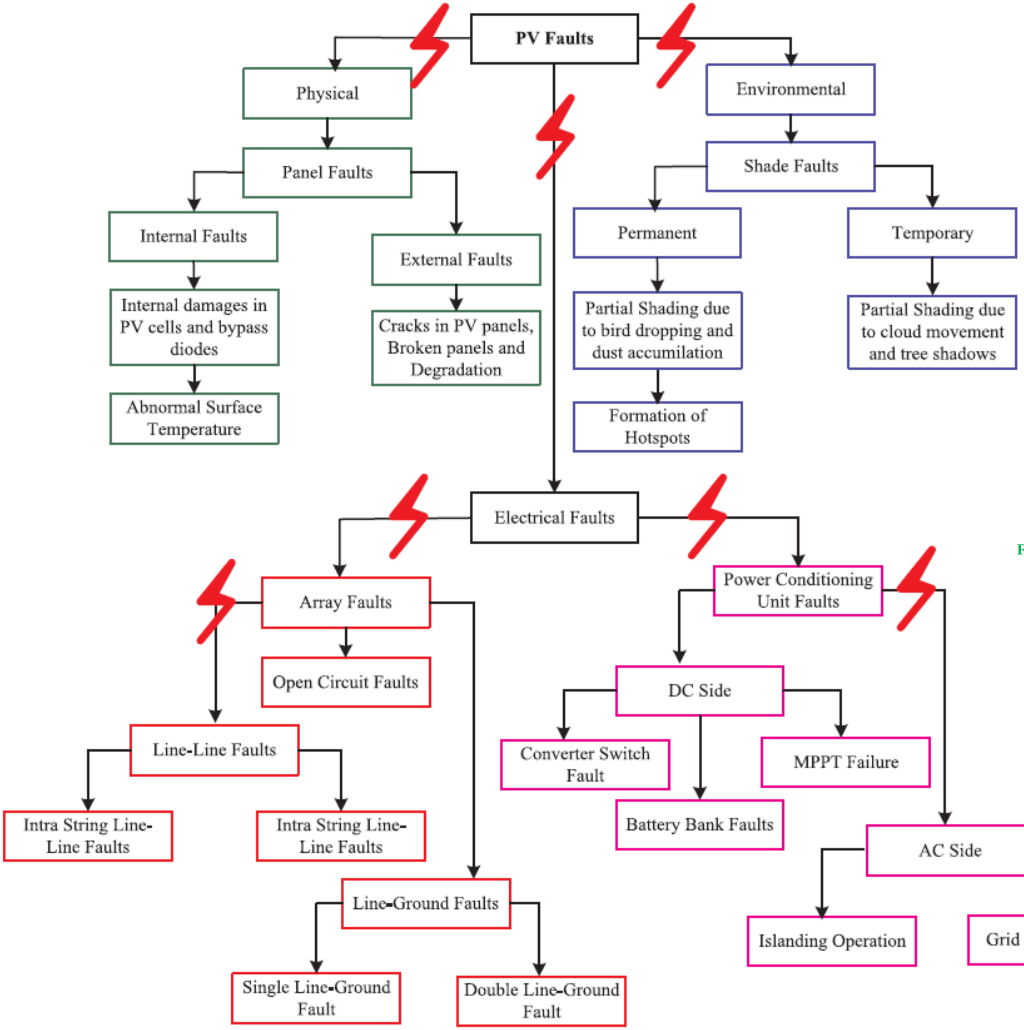


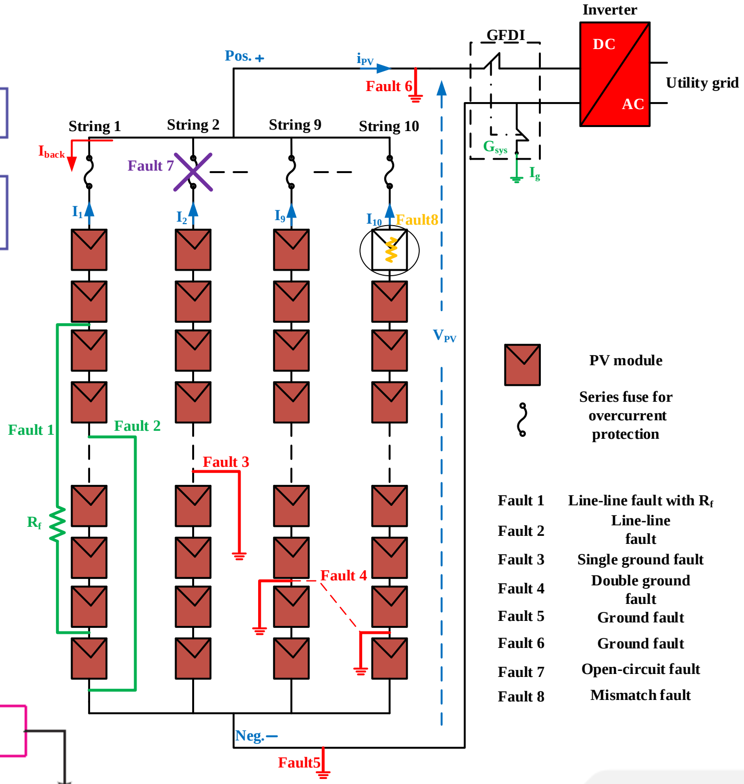


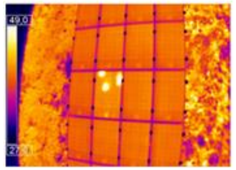
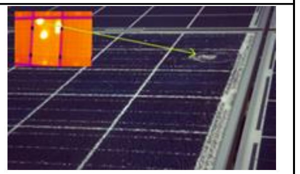
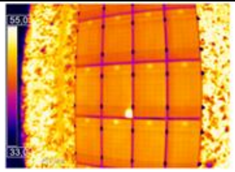
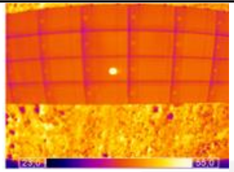
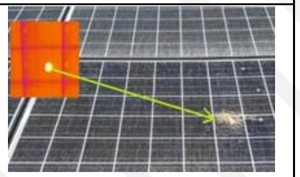
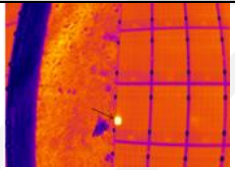
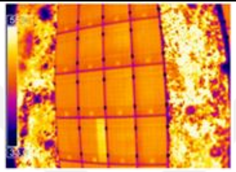
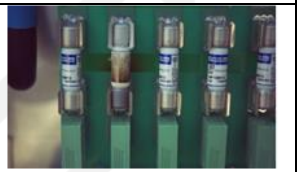
Natural processes affecting soiling of PV modules and subsequent power loss.

PV Performance Modeling Methods and Practices ,Results from the 4th PV Performance Modeling Collaborative Workshop, PVPS, IEA, 2017.

Defects and Failures in PV modules, components and systems



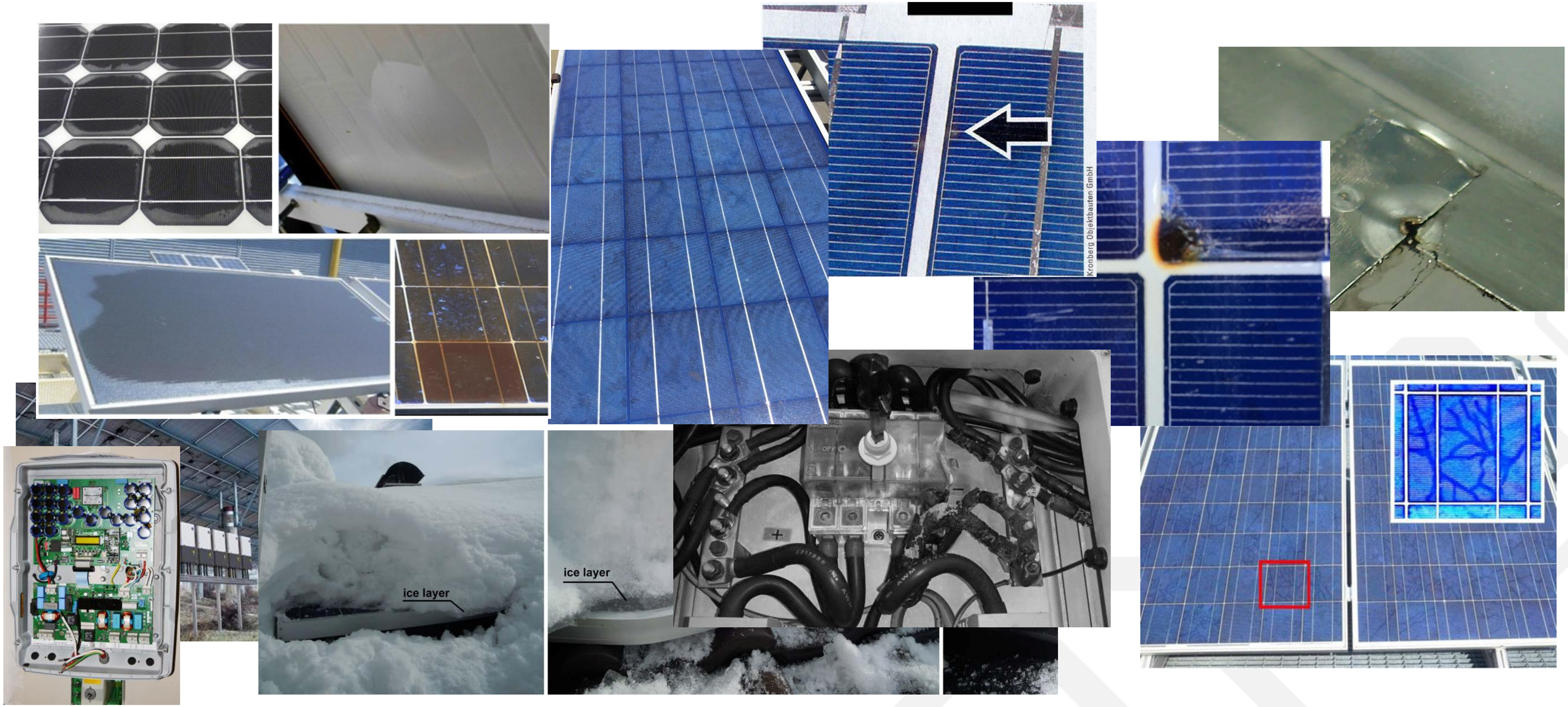


Defect	Low altitude aerial image (IR)	Ground Truthing (visual)
Severe glass and cell fractures		
Cracked cell		
Excessive soiling and dirt, resulting in severe hot spots and power losses		
Shading by adjacent vegetation, resulting in electrical mismatch, hot spot and power losses		
PV modules diagnosed with bypass diode failures. Hard to detect on the ground but clearly identifiable from the air.		

Environmental conditions, Human errors, Shading, Soiling, Inverter clipping, Power factor correction, Module/string faults, Degradation and etc.

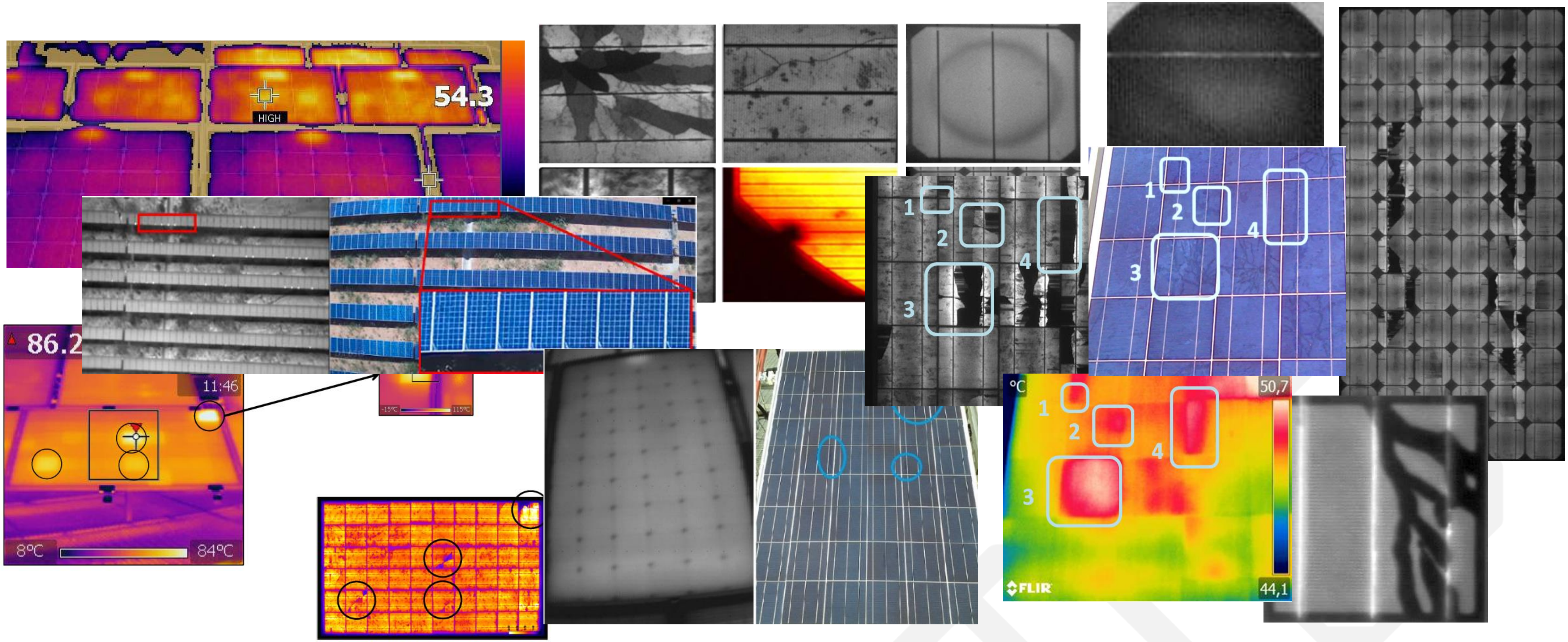
- D. S. Pillai and N. Rajasekar, "A comprehensive review on protection challenges and fault diagnosis in PV systems," Renewable and Sustainable Energy Reviews. 2018.
- A.K. Oliveira, M. Aghaei, R.Ricardo, Aerial infrared thermography for low-cost and fast fault detection in utility-scale PV power plants, Solar Energy, 2020.
- A.Eskandary, J. Milimonfared, M. Aghaei, "Line-to-Line Faults Detection for Photovoltaic Arrays Based on I-V Curve Using Pattern Recognition", 46th IEEE PVSC, Chicago, USA, June, 2019.
- IEA-PVPS, Subtask 3.2: Good Practice Recommendations to Qualify PV Power Plants using Mobile Devices, 2021.

Defects and Failures in PV modules, components and systems



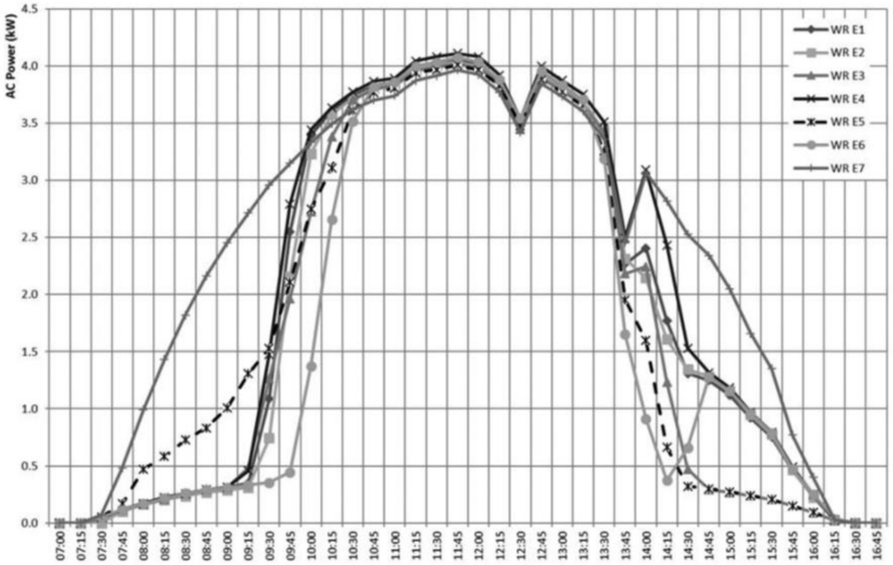
-P. Bellezza Quater, F. Grimaccia, S. Leva, M. Mussetta, M. Aghaei, "Light Unmanned Aerial Vehicles (UAVs) for Cooperative Inspection of PV Plants", IEEE Journal of Photovoltaics.
-S. Leva and M. Aghaei, "Failures and Defects in PV Systems Review and Methods of Analysis," 2018, pp. 56–84.

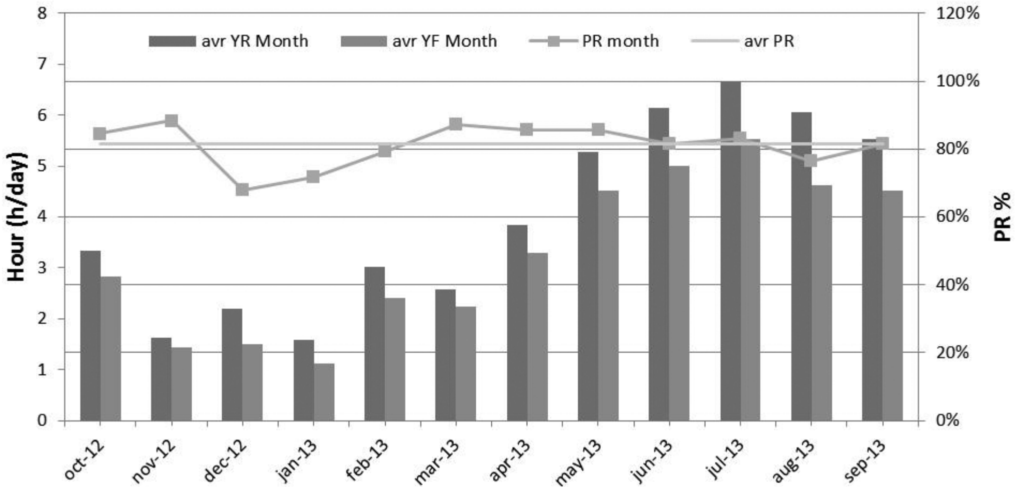
Defects and Failures in PV modules, components and systems

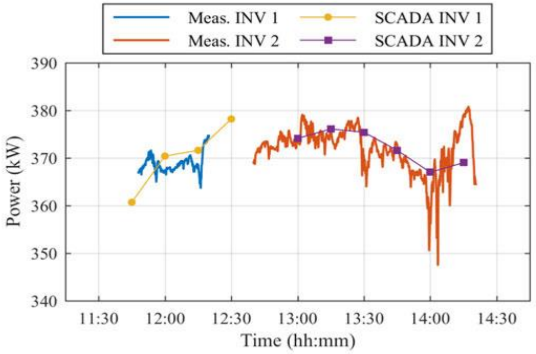


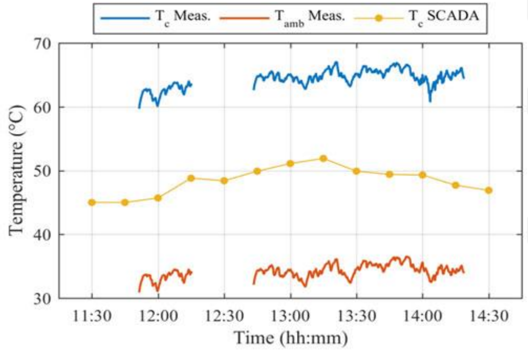
-P. Bellezza Quater, F. Grimaccia, S. Leva, M. Mussetta, M. Aghaei, "Light Unmanned Aerial Vehicles (UAVs) for Cooperative Inspection of PV Plants", IEEE Journal of Photovoltaics.
-M.Köntges, S. Kurtz, C. Packard, U. Jahn, K.A. Berger, Ka. Kato, T. Friesen, "Review of failures of Photovoltaic Modules, " IEA-PVPS T13-01: 2014.
-S. Leva and M. Aghaei, "Failures and Defects in PV Systems Review and Methods of Analysis," 2018, pp. 56–84.

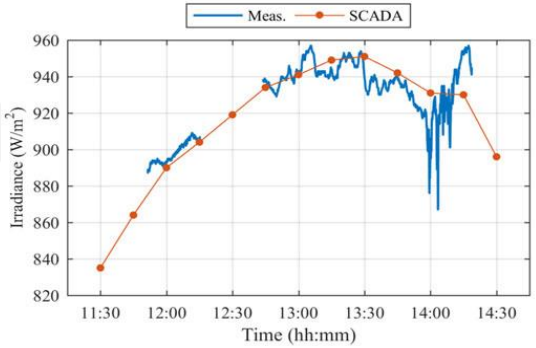
Defects and Failures in PV modules, components and systems

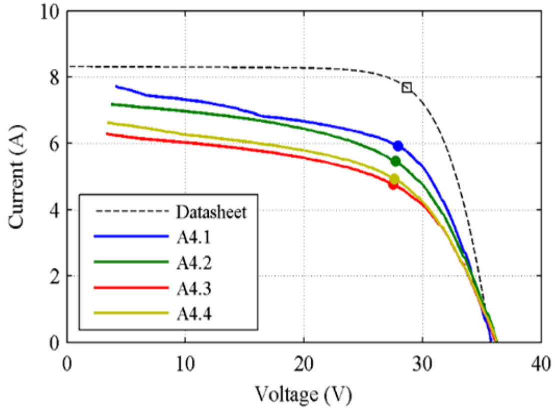


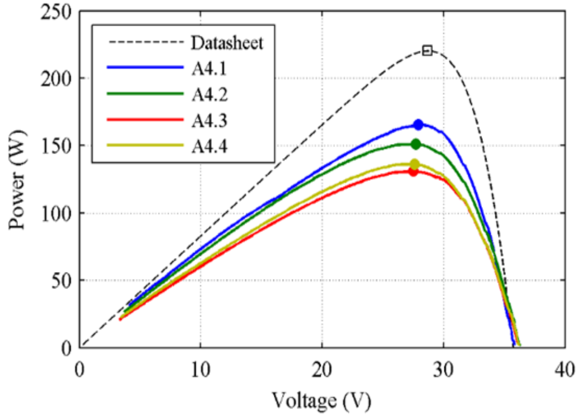


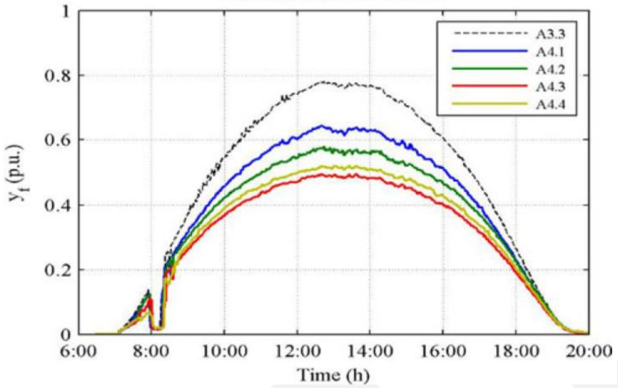








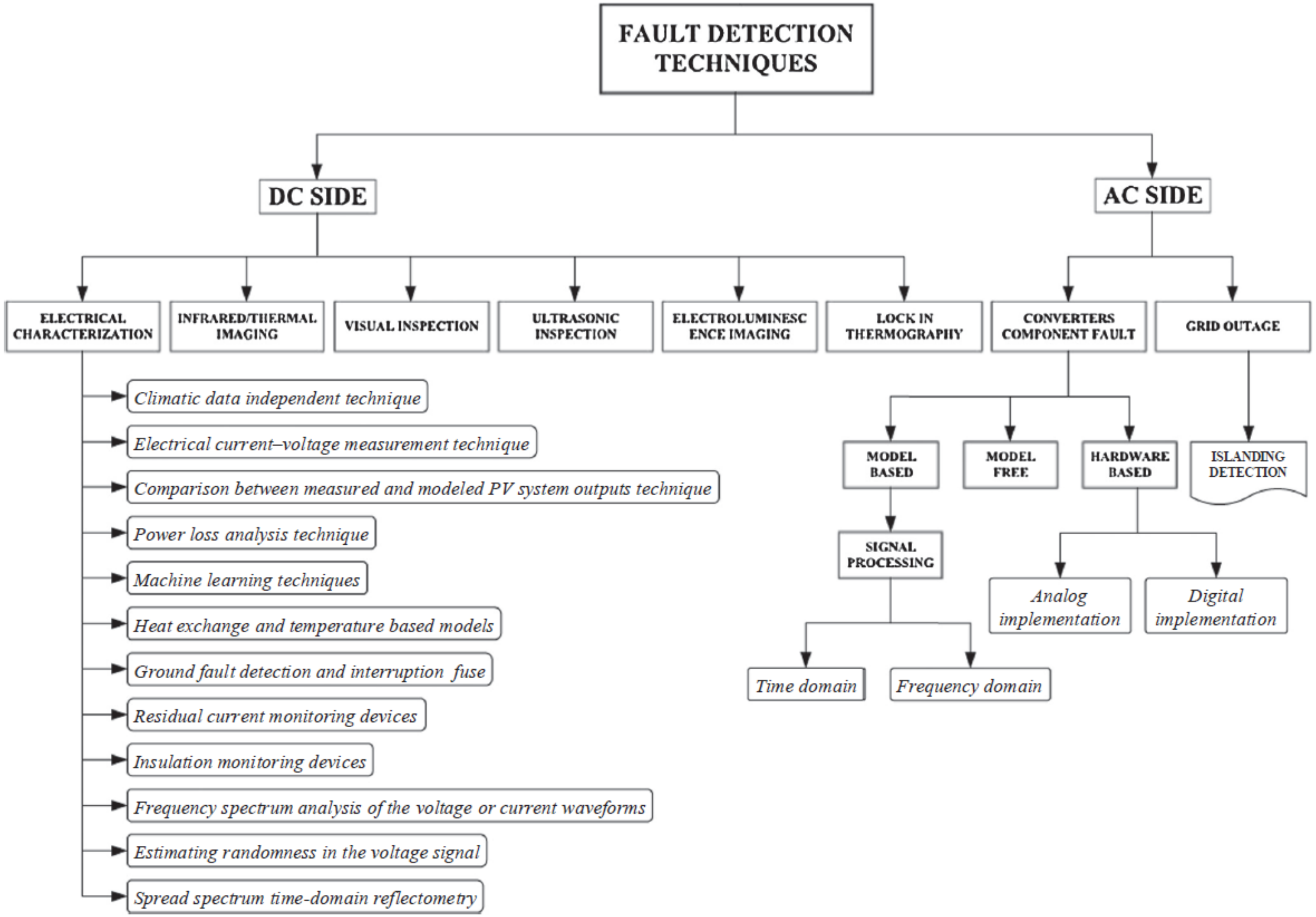




-P. Bellezza Quater, F. Grimaccia, S. Leva, M. Mussetta, M. Aghaei, "Light Unmanned Aerial Vehicles (UAVs) for Cooperative Inspection of PV Plants", IEEE Journal of Photovoltaics.
-M. Aghaei, "Novel Methods in Control and Monitoring of Photovoltaic Systems", Ph.D Thesis, Politecnico di Milano, 2016.
-S. Leva and M. Aghaei, "Failures and Defects in PV Systems Review and Methods of Analysis," 2018, pp. 56–84.
F. Grimaccia, Alberto Dolara, S. Leva, M. Aghaei (2016): "Survey on PV Modules' Common Faults After an O&M Flight Extensive Campaign Over Different Plants in Italy", IEEE Journal of Photovoltaics, 2017.

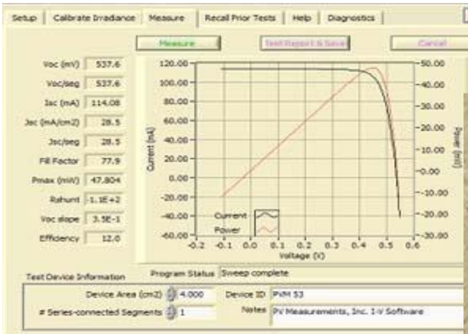
Failure detection techniques

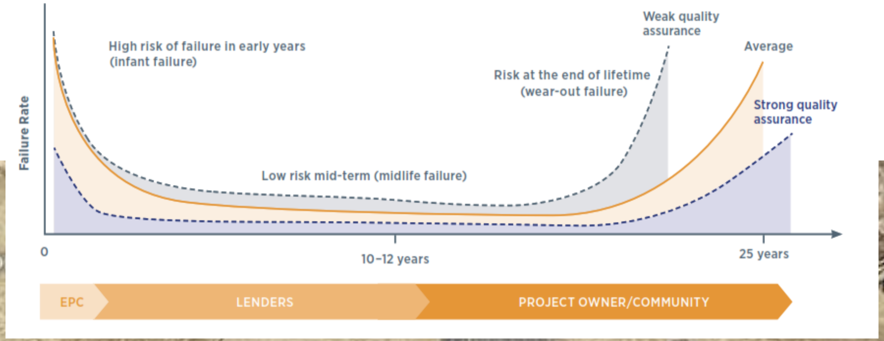
- ➢ Visual detection
- ❖ Delamination, Bubbles, Cracking, Yellowing, Discoloration, Oxidation, Cell breakage
- ➢ Infrared thermography analysis
- ❖ Snail trails , Hot spots, Micro cracks, Corrosion of connectors
- ➢ Electrical characterization
- ❖ Shading, Hot spots
- ➢ Electroluminescence, Photoluminescence and UV-Flourescence
- ❖ Hot spots, Micro cracks
- ➢ Signal Transmission Device (STD) Technique
- ❖ interconnect ribbons, bypass diode failure
- ➢ Novel methods
- ❖ UAV application, Smart monitoring and intelligent fault diagnosis (AI/machine learning).

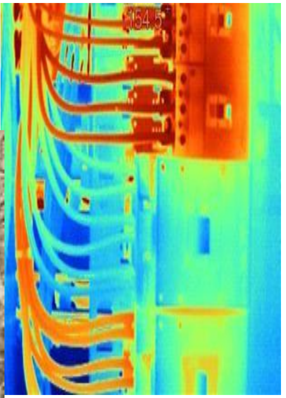


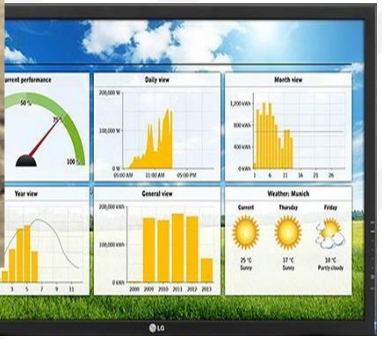
-P. Bellezza Quater, F. Grimaccia, S. Leva, M. Mussetta, M. Aghaei, "Light Unmanned Aerial Vehicles (UAVs) for Cooperative Inspection of PV Plants", IEEE Journal of Photovoltaics.
-S. R. Madeti and S. N. Singh, "A comprehensive study on different types of faults and detection techniques for solar photovoltaic system," Sol. Energy, vol. 158, pp. 161–185, 2017.

Why is intelligent fault diagnosis for PV system important?



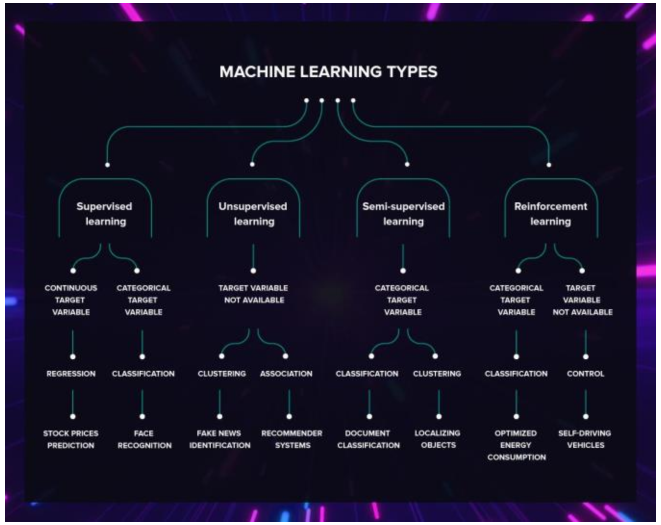


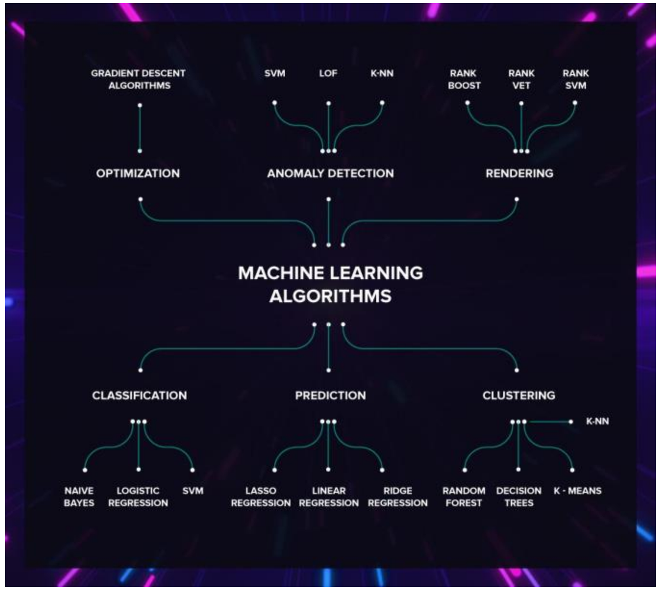


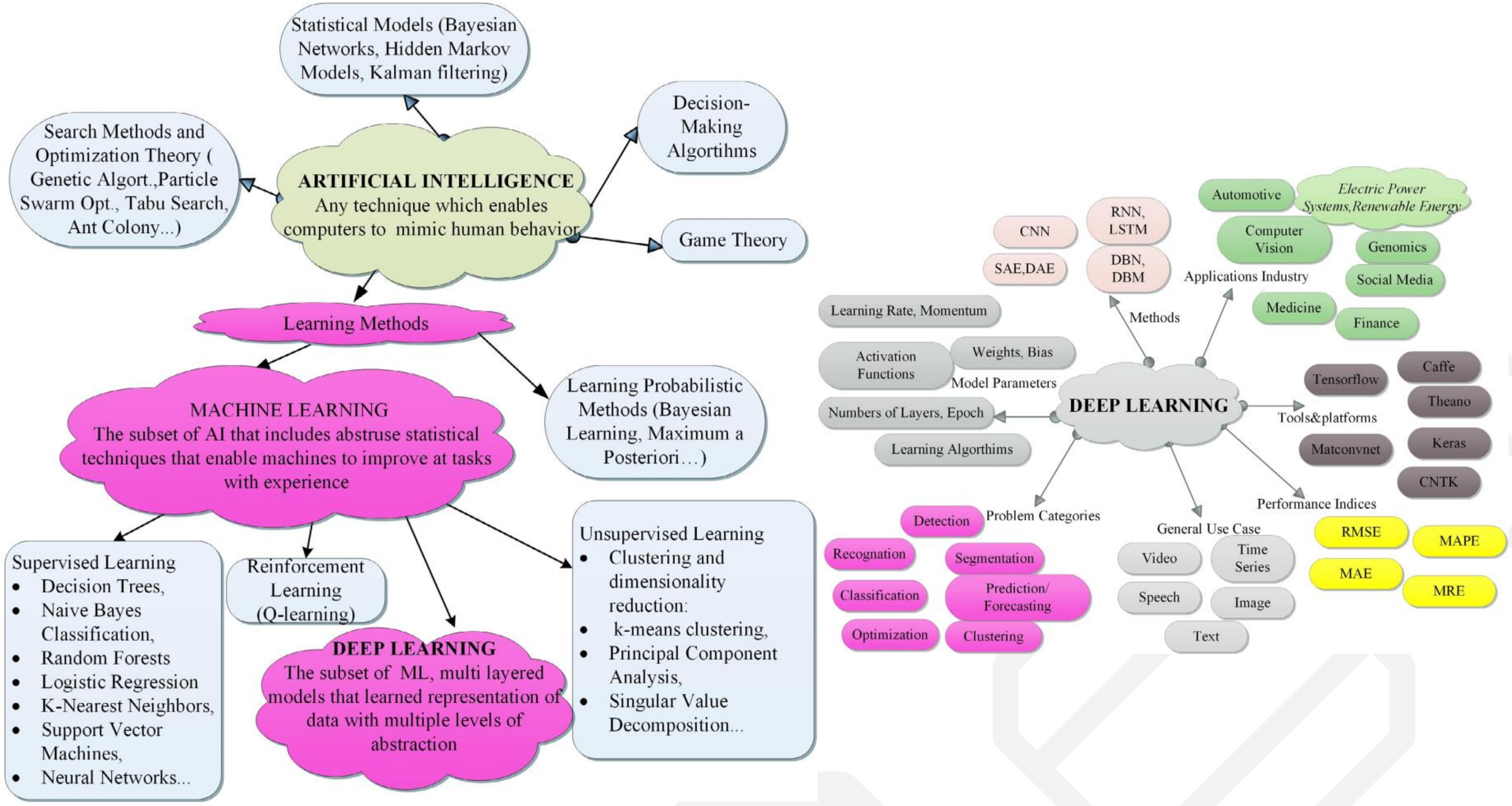


-BOOSTING SOLAR PV MARKETS: THE ROLE OF QUALITY INFRASTRUCTURE, 2017
-https://www.originenergy.com.au/blog/lifestyle/5-largest-solar-farms-in-the-world.html

Artificial Intelligence (AI) techniques



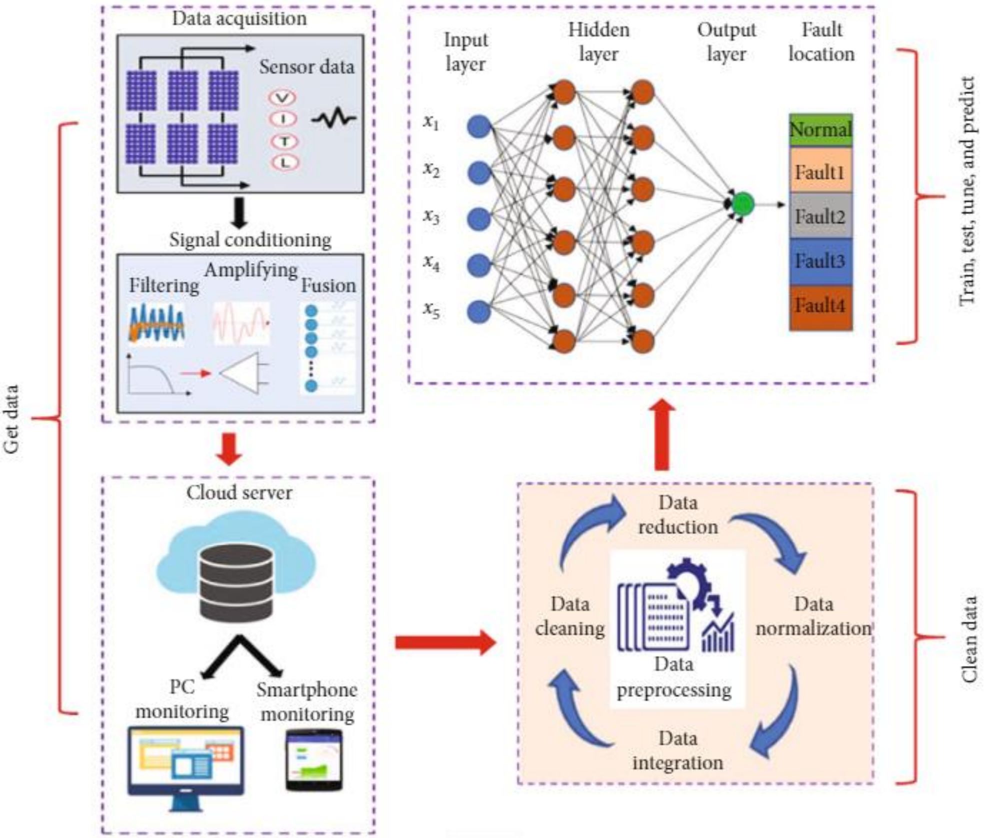


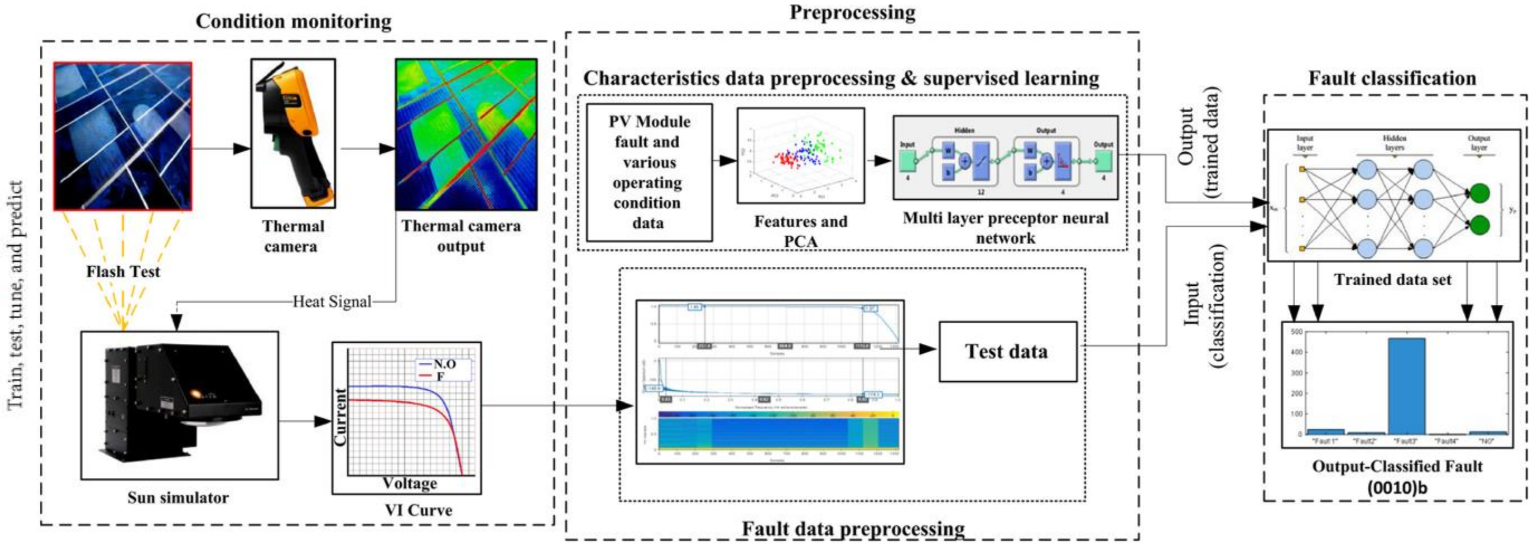


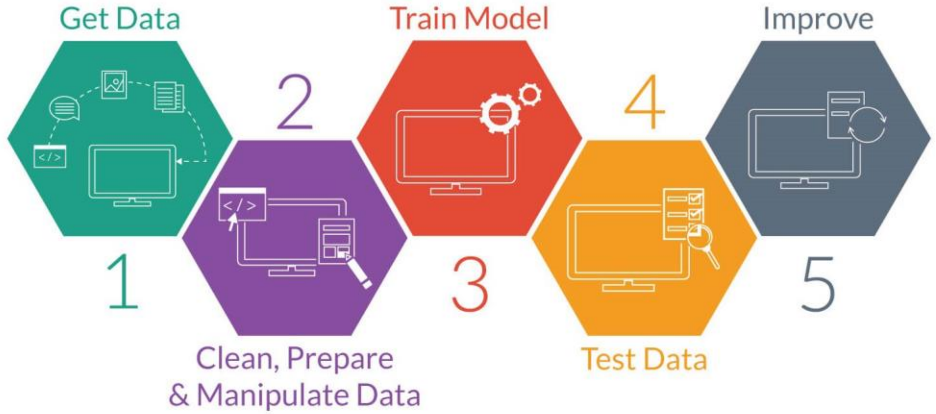
Development and milestones of Intelligent fault diagnosis using machine learning

- Yaguo Lei et al. Applications of machine learning to machine fault diagnosis: A review and roadmap, Mechanical Systems and Signal Processing, 2020.
- https://serokell.io/blog/how-to-choose-ml-technique, access: 5th July 2021.
- A. K. Ozcanli, F. Yaprakdal, and M. Baysal, "Deep learning methods and applications for electrical power systems: A comprehensive review," Int. J. Energy Res., vol. 44, no. 9, pp. 7136–7157, 2020.

Machine learning process for faults detection in PV systems

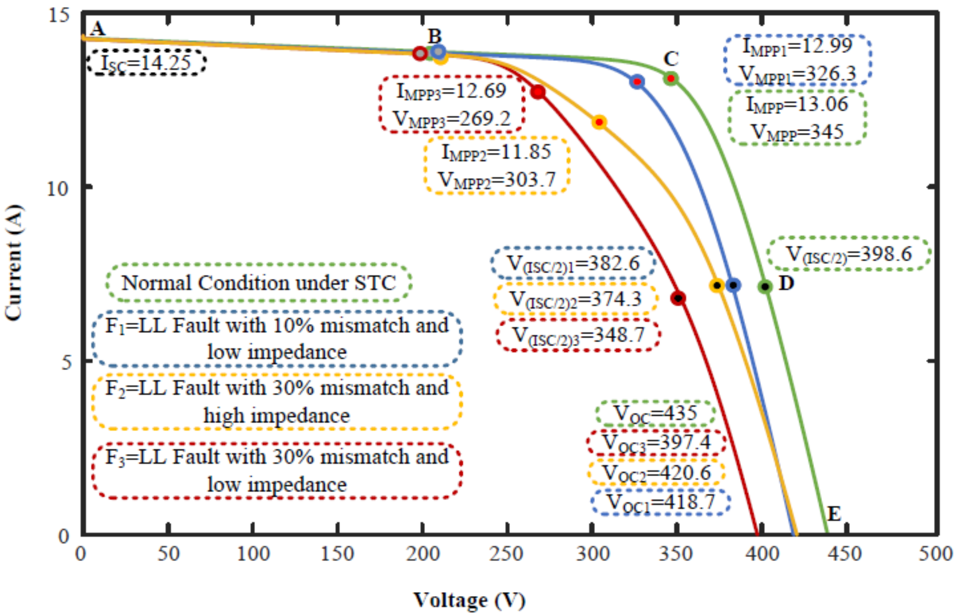




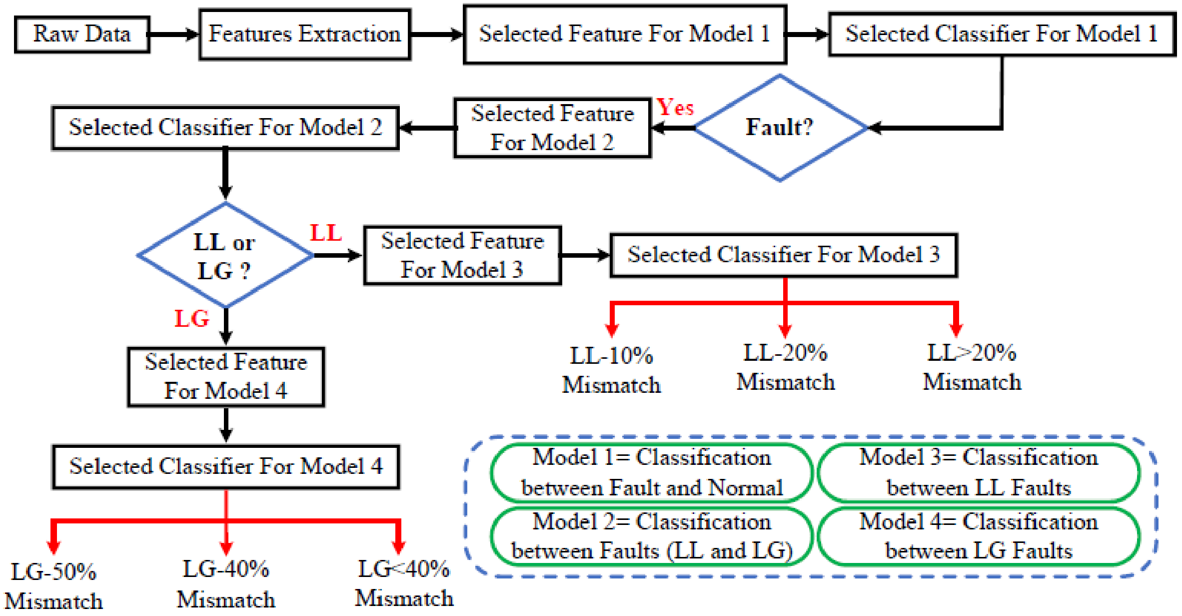


-Basnet B, Chun H, Bang J. An intelligent fault detection model for fault detection in photovoltaic systems. J Sensors 2020.
-Haque A, Bharath KVS, Khan MA, Khan I, Jaffery ZA. Fault diagnosis of Photovoltaic Modules. Energy Sci Eng 2019.
-https://centricconsulting.com/blog/machine-learning-a-quick-introduction-and-five-core-steps/

Electrical faults (DC side) detection/classification in PV systems using machine learning techniques



I-V characteristics of PV array under normal condition, and LL fault under low and high mismatch level with and without impedance



Extracted features		
$f_1 = I_{SC}/I_{SC(STC)}$	$f_2 = V_{OC}/V_{OC(STC)}$	$f_3 = V_{MPP}/V_{MPP(STC)}$
$f_4 = I_{MPP}/I_{MPP(STC)}$	$f_5 = I_{\frac{V_{OC}}{2}}/I_{SC(STC)}$	$f_6 = V_{\frac{I_{SC}}{2}}/V_{OC(STC)}$
$f_7 = f_4/f_3$	$f_8 = f_3/f_2$	$f_9 = f_4/f_1$
$f_{10} = (I_{MPP}-I_{SC})/(V_{MPP})$		$f_{11} = (-I_{MPP})/(V_{OC}-V_{MPP})$
$f_{12} = (I_{\frac{V_{OC}}{2}}-I_{SC})/(\frac{V_{OC}}{2})$		$f_{13} = (I_{MPP}-I_{\frac{V_{OC}}{2}})/(V_{MPP}-\frac{V_{OC}}{2})$
$f_{14} = (\frac{I_{SC}}{2}-I_{MPP})/(V_{\frac{I_{SC}}{2}}-V_{MPP})$		$f_{15} = (-\frac{I_{SC}}{2})/(V_{OC}-V_{\frac{I_{SC}}{2}})$
$f_{16} = \frac{FF}{FF_{(STC)}} \rightarrow FF=\frac{V_{MPP}\times I_{MPP}}{V_{OC}\times I_{SC}}, FF_{(STC)}=\frac{V_{MPP(STC)}\times I_{MPP(STC)}}{V_{OC(STC)}\times I_{SC(STC)}}$		

Features extraction procedure

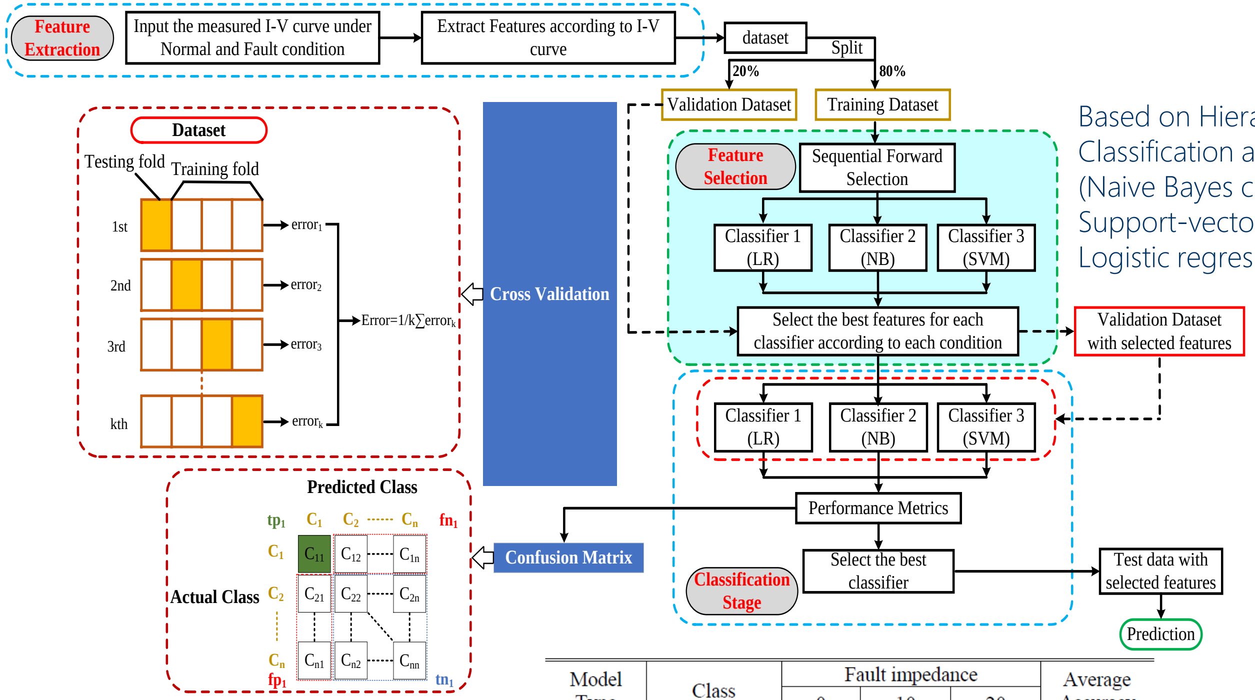
Variable	Values	
	Training dataset	Test dataset
Operation Temperature (°C)	0, 5, 10, 15, 20, 25, 30, 35, 40	4, 7, 12, 17, 22, 27, 33,38
Irradiance Level (W/m²)	200, 400, 600, 800, 1000	350, 550, 900
Mismatch Percentage (%)	10, 20, 30, 40, 50	10, 20, 30, 40, 50
Fault Impedances (Ω)	0, 5, 10, 15, 20, 25	3, 7, 12, 22

Training and testing dataset under various conditions

-A. Eskandari, J. Milimonfared, and M. Aghaei, "Fault Detection and Classification for Photovoltaic Systems Based on Hierarchical Classification and Machine Learning Technique," IEEE Trans. Ind. Electron., 2020.
-A. Eskandari, J. Milimonfared, and M. Aghaei, "Line-Line Fault Detection and Classification for Photovoltaic Systems using Ensemble Learning Model Based on I-V Characteristics," Sol. Energy, 2020.
-A Eskandari, J. Milimonfared, M. Aghaei, and A. H. M. E. Reinders, "Autonomous Monitoring of Line-to-Line Faults in Photovoltaic Systems by Feature Selection and Parameter Optimization of Support Vector Machine Using Genetic Algorithm," Appl. Sci., 2020.

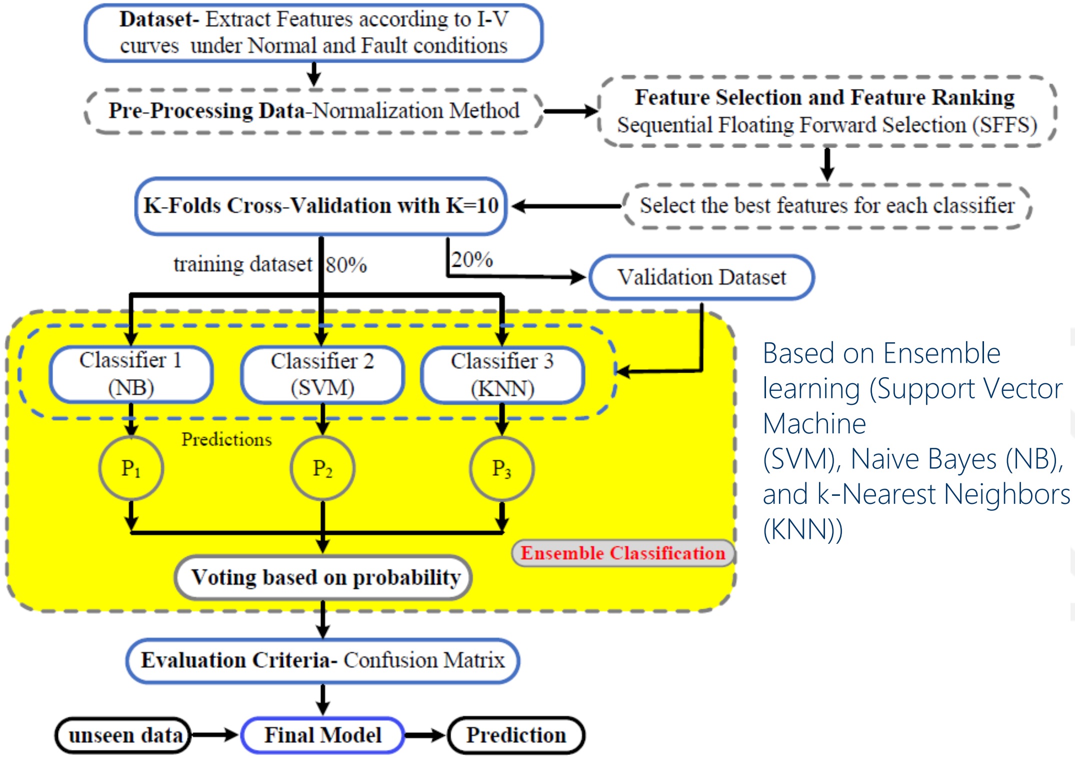
Electrical faults (DC side) detection/classification in PV systems using machine learning techniques

- Automatic electrical fault detection and classification for PV Systems using various machine learning techniques.
  Datasets: 1200 L-L and L-G fault and also normal events.
  Accuracy: 97%, 99.5%



Based on Hierarchical Classification and MLT (Naive Bayes classifier, Support-vector machine, Logistic regression)

Model Type	Class	Fault impedance 0	10	20	Average Accuracy
1	Fault	40/40	40/40	38/40	98.33%
2	LL	20/20	20/20	18/18	100%
	LG	20/20	19/20	18/20	95%
3	LL- 16.67%	10/10	10/10	8/8	100%
	LL- 33.3%	10/10	10/10	10/10	100%
4	LG- 66.67%	10/10	10/10	7/9	93.1%
	LG- 50%	10/10	9/9	9/9	100%
Final Success	LL	58/60			96.66%
	LG	55/60			91.66%



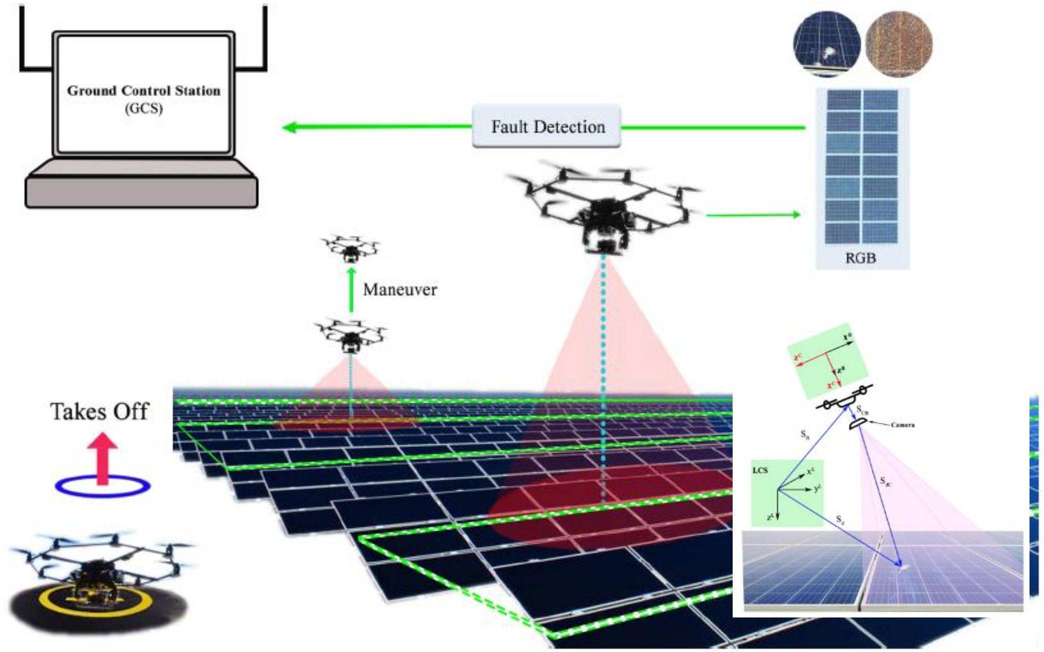
Based on Ensemble learning (Support Vector Machine (SVM), Naive Bayes (NB), and k-Nearest Neighbors (KNN))

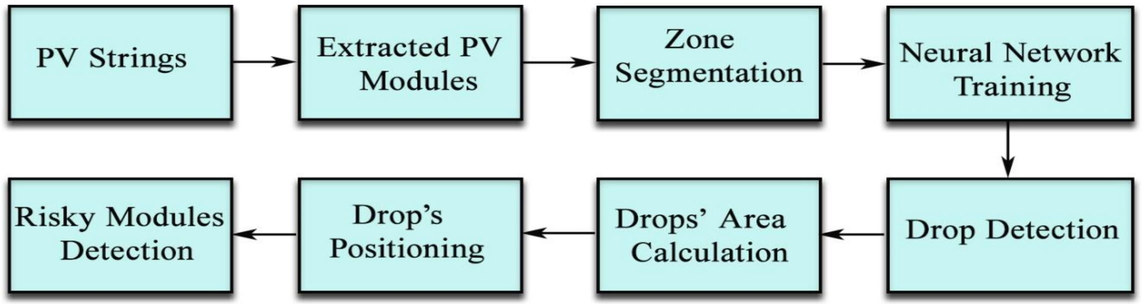
Model Type	Training accuracy (standard deviation)	Confusion matrix	Testing accuracy
FD	98.88% (0.63%)	$\begin{bmatrix} 60 & 0 \\ 1 & 71 \end{bmatrix}$	99.24%
LLC	99.06% (0.677%)	$\begin{bmatrix} 24 & 0 & 0 \\ 0 & 24 & 0 \\ 0 & 0 & 24 \end{bmatrix}$	100%

-A. Eskandari, J. Milimonfared, and M. Aghaei, "Fault Detection and Classification for Photovoltaic Systems Based on Hierarchical Classification and Machine Learning Technique," IEEE Trans. Ind. Electron., 2020.
-A. Eskandari, J. Milimonfared, and M. Aghaei, "Line-Line Fault Detection and Classification for Photovoltaic Systems using Ensemble Learning Model Based on I-V Characteristics," Sol. Energy, 2020.
-A Eskandari, J. Milimonfared, M. Aghaei, and A. H. M. E. Reinders, "Autonomous Monitoring of Line-to-Line Faults in Photovoltaic Systems by Feature Selection and Parameter Optimization of Support Vector Machine Using Genetic Algorithm," Appl. Sci., 2020.

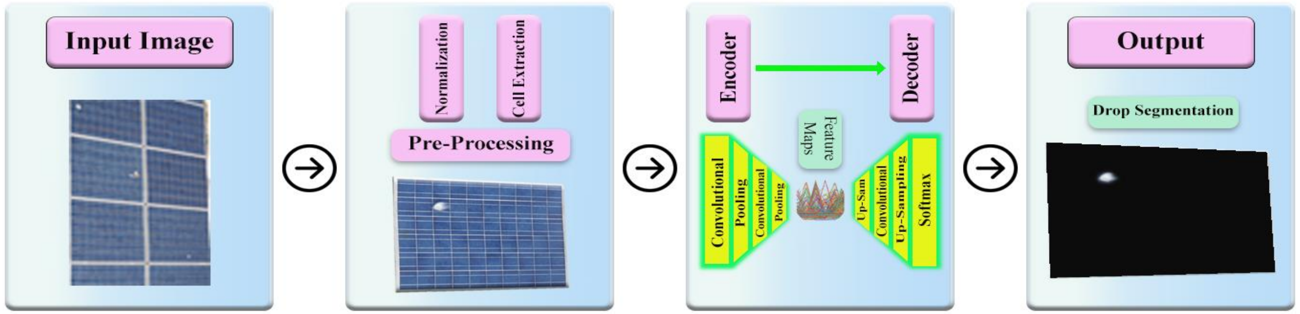
Defects / failures (visible) detection in PV strings using fully convolutional network (FCN)

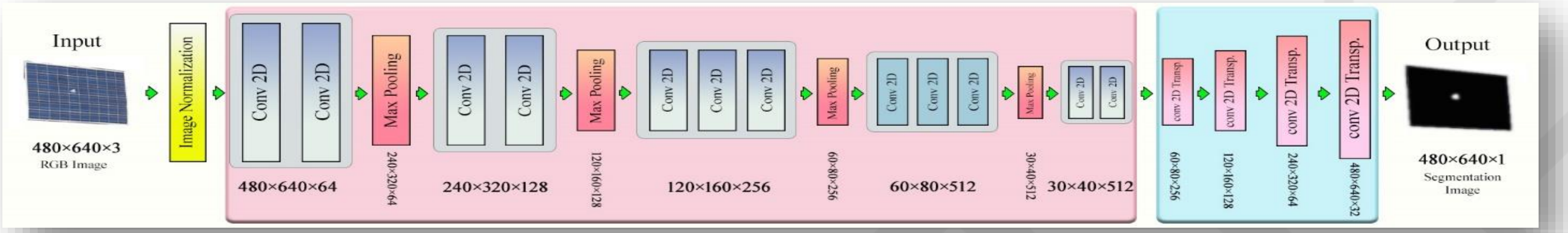
- Automatic faults detection procedure by CNN during Aerial visual inspection.
- Dataset: more than 1000 aerial RGB images.
  Accuracy: 93%.





The essential steps of drop segmentation

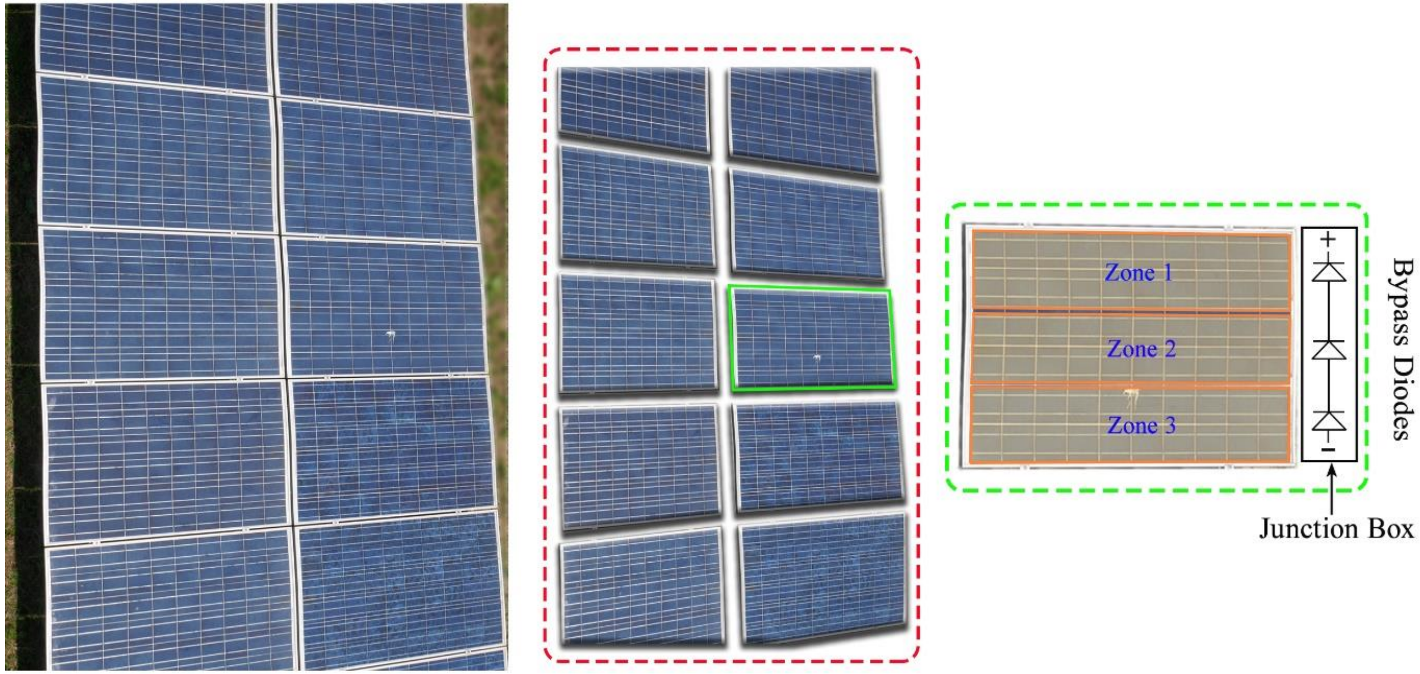




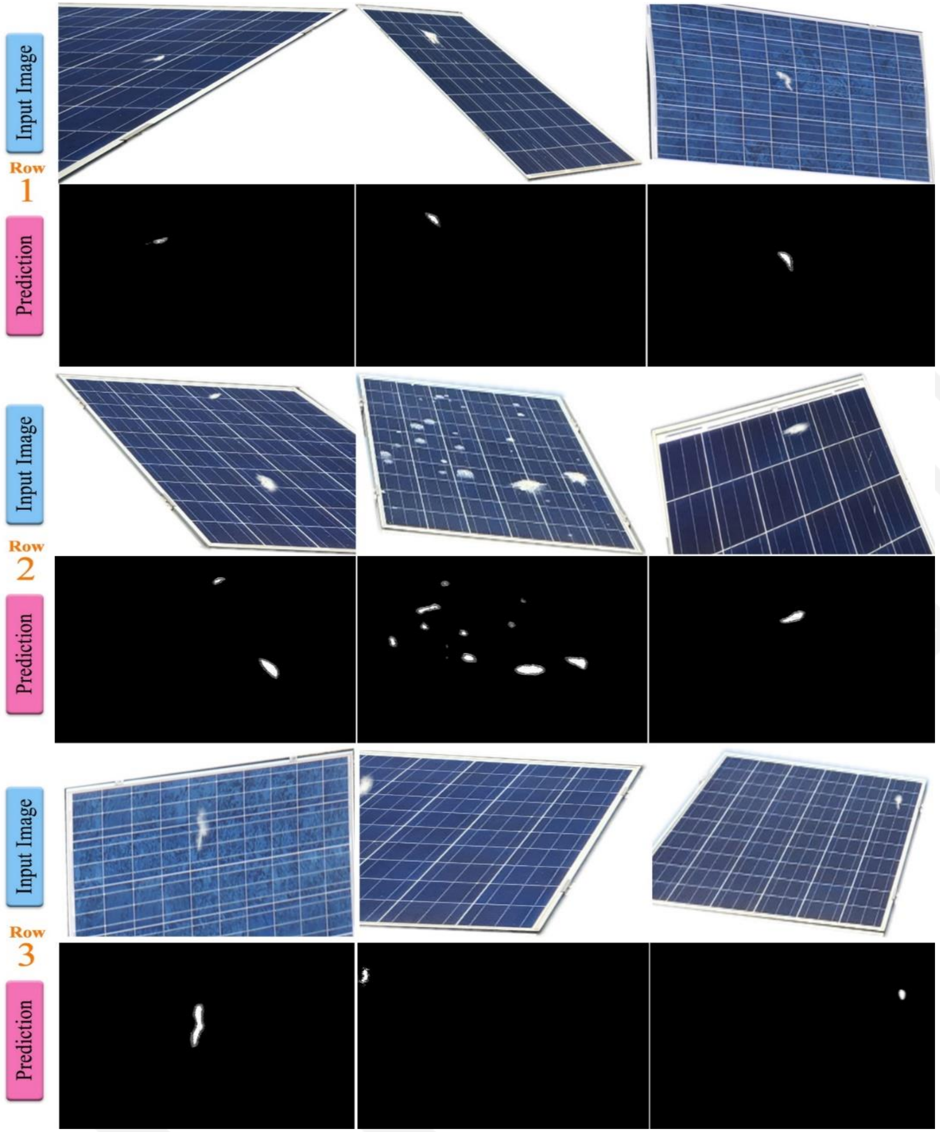
Deep Model Configuration

A.M. Moradi, M. Aghaei, S.M.Esmailifar " A deep convolutional encoder-decoder architecture for autonomous fault detection of PV plants using multi-copters ", Solar Energy, PP. 217 – 228, 2021.

Defects/failures (visible) detection in PV strings using fully convolutional network (FCN)



PV String (a) Extracted Modules (b) Zones Segmentation (c)



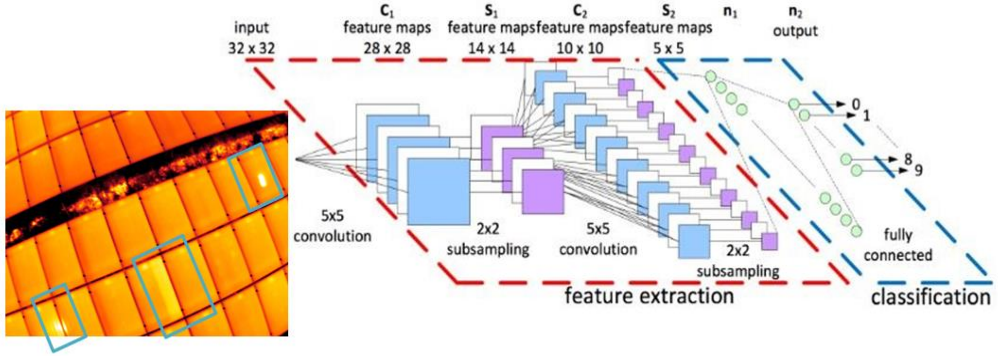
- 1000 extracted images of affected PV modules
  - 85% are dedicated to training and validation

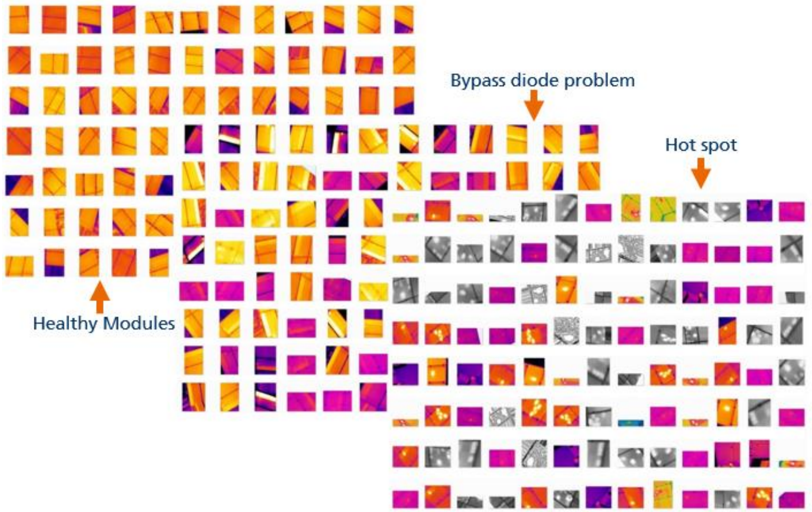
Activations	Pixel Accuracy	Jaccard (IoU) Score	Dice (F1) Score
TanH	0.91	0.42	0.61
ELU	0.93	0.42	0.62
Sigmoid	0.95	0.46	0.62

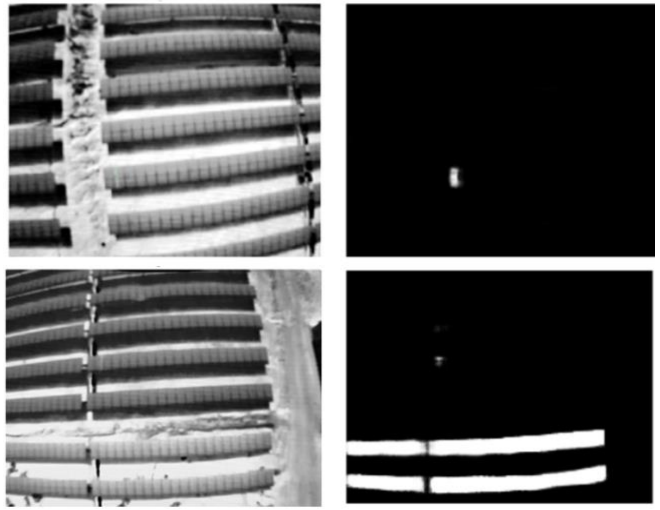
A.M. Moradi, M. Aghaei, S.M.Esmailifar " A deep convolutional encoder-decoder architecture for autonomous fault detection of PV plants using multi-copters ", Solar Energy, PP. 217 – 228, 2021.

Failures (IR) detection in PV strings using convolutional neural network (CNN)

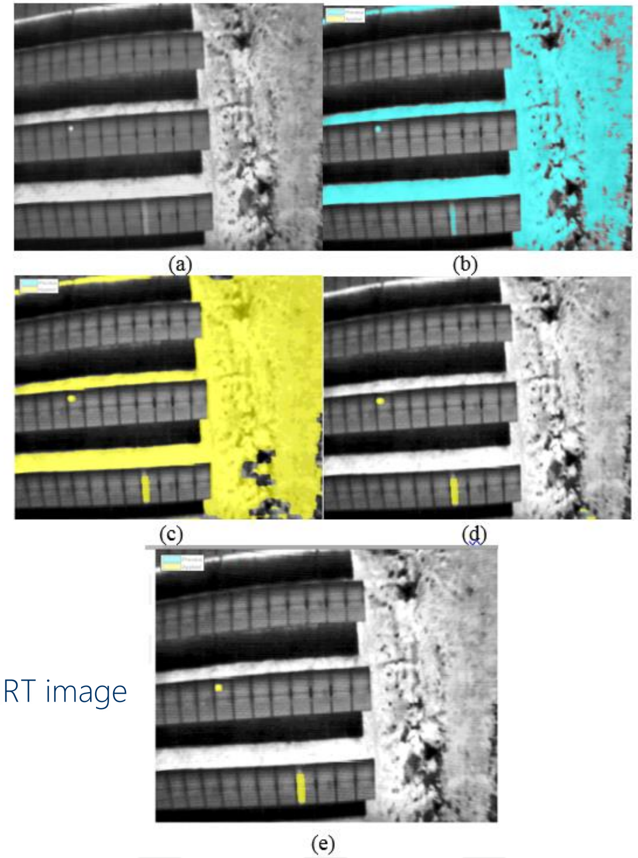
- Automatic fault detection procedure by CNN during Aerial Infrared Thermography.
  Dataset: more than 3300 aerial IR images.
  Accuracy: 90%.







Steps of the segmentation of faults in an aIRT image

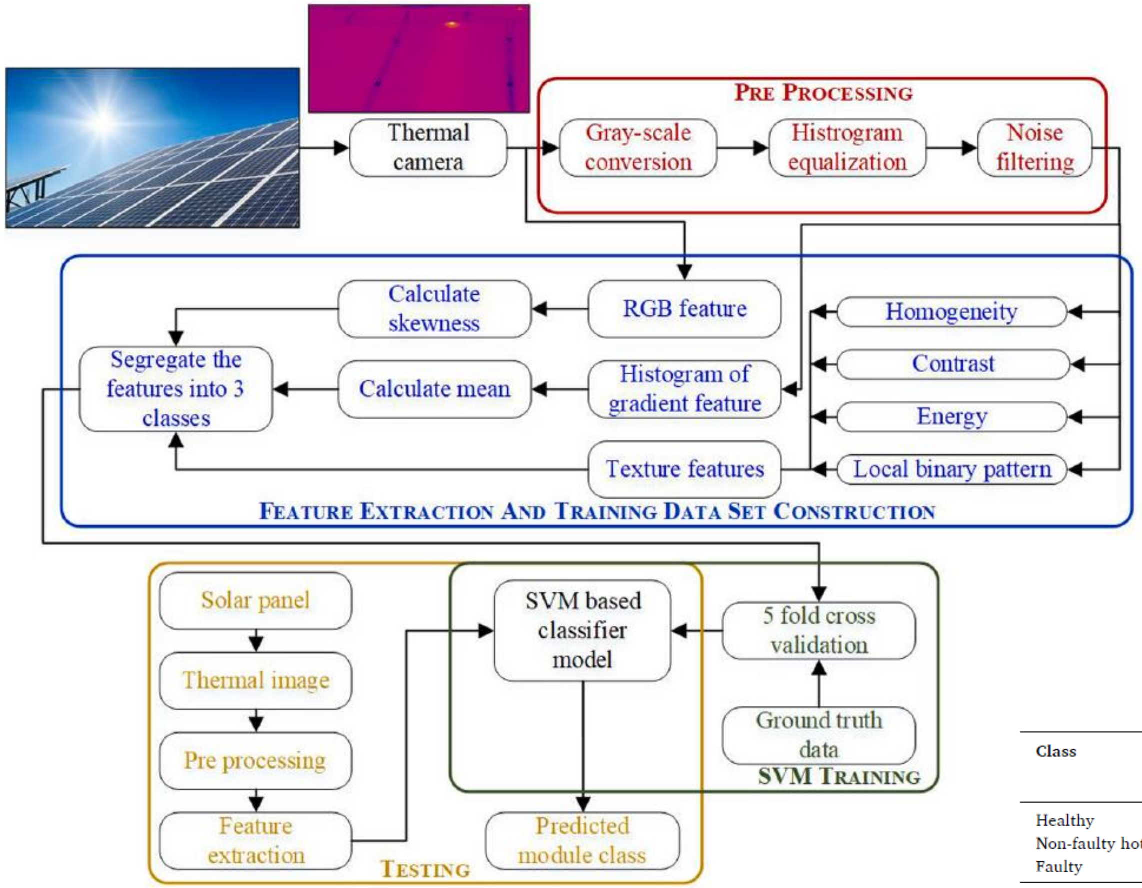


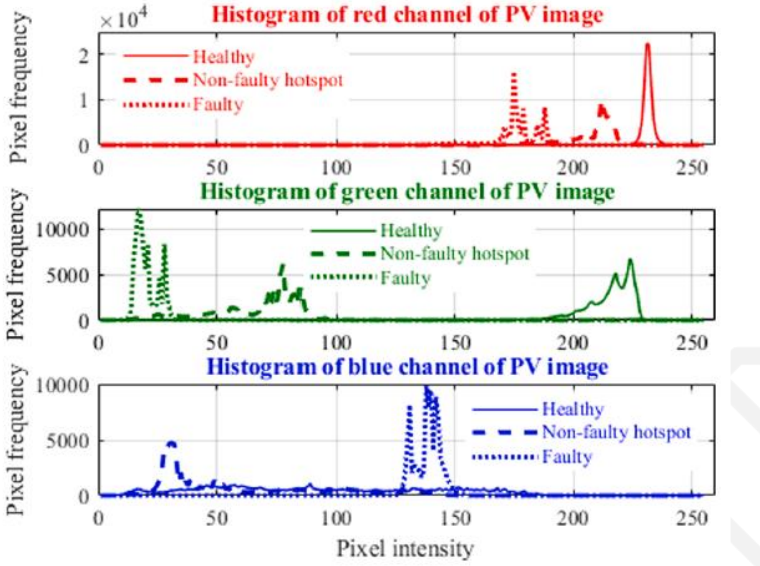
-A.K. Oliveira, M. Aghaei, R.Ricardo "Automatic Fault Detection of Photovoltaic Array by Convolutional Neural Networks during Aerial Infrared Thermography", 36th EUPVPES, France, September, 2019.

M. Aghaei, A. Eskandari, and A. H. M. E. Reinders, “Autonomous Monitoring and Analysis of PV Systems by Unmanned Aerial Vehicles, Internet of Things and Big Data Analytics,” in 37th EUPVSEC, 2020

Failures (IR) detection in PV strings using support vector machine (SVM)

- Fault detection procedure by SVM during Infrared Thermography.
  Dataset: more than 310 IR images.
  Accuracy: 92%.





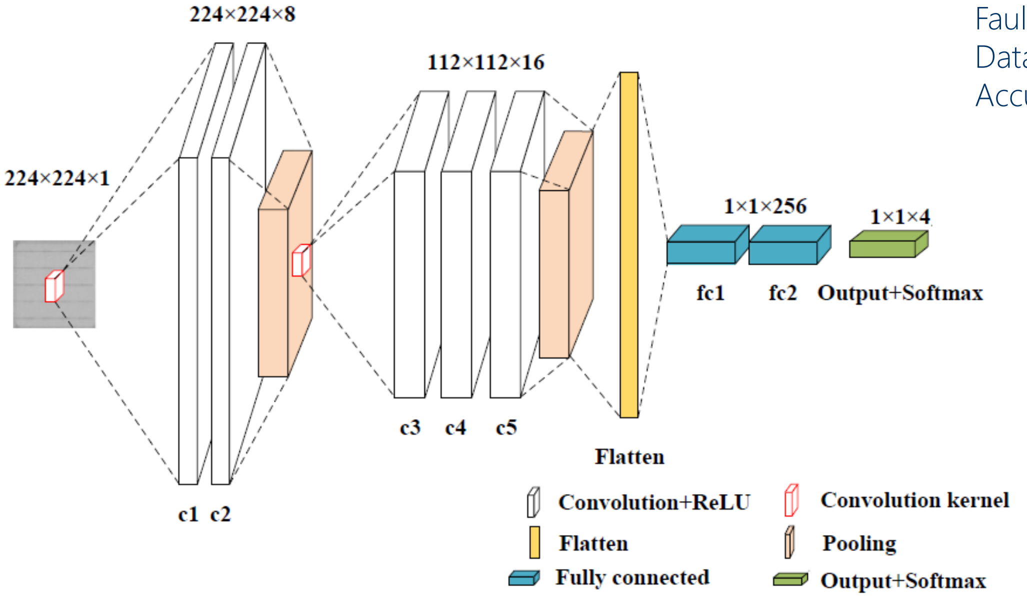
RGB histograms under different PV module conditions

PV panel categorization	Number of images
Healthy class	102
Non-faulty hotspot class	99
Faulty class	114

Class	Classified as			TPR	FNR	PPV	FDR	Accuracy(%)
	Healthy	Non-faulty hotspot	Faulty					
Healthy	**26**	1	0	96.29	3.71	89.65	10.35	92.00
Non-faulty hotspot	2	**23**	1	88.46	11.54	92.00	8.00	
Faulty	1	1	**20**	90.90	9.10	95.23	4.77	

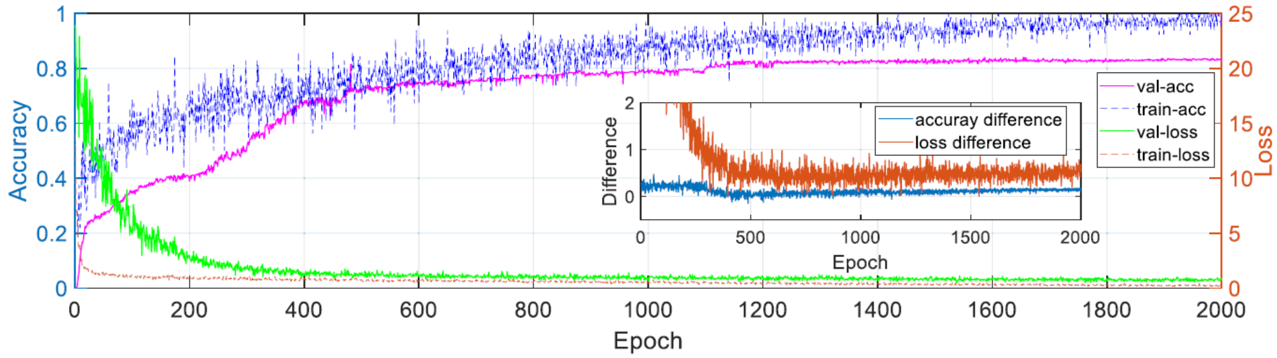
Ali MU, Khan HF, Masud M, Kallu KD, Zafar A. A machine learning framework to identify the hotspot in photovoltaic module using infrared thermography. Sol Energy 2020;208:643–51.

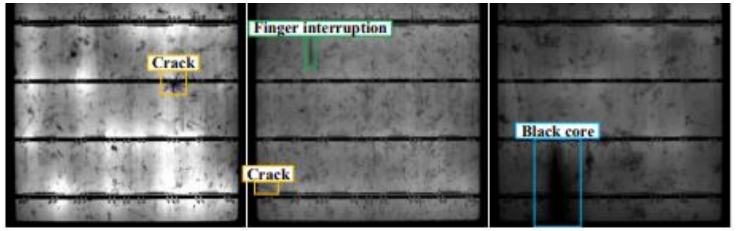
Failures (EL) detection in PV strings using generative adversarial network (GAN) and convolutional neural network (CNN)



Architecture of CNN based model for defect classification.

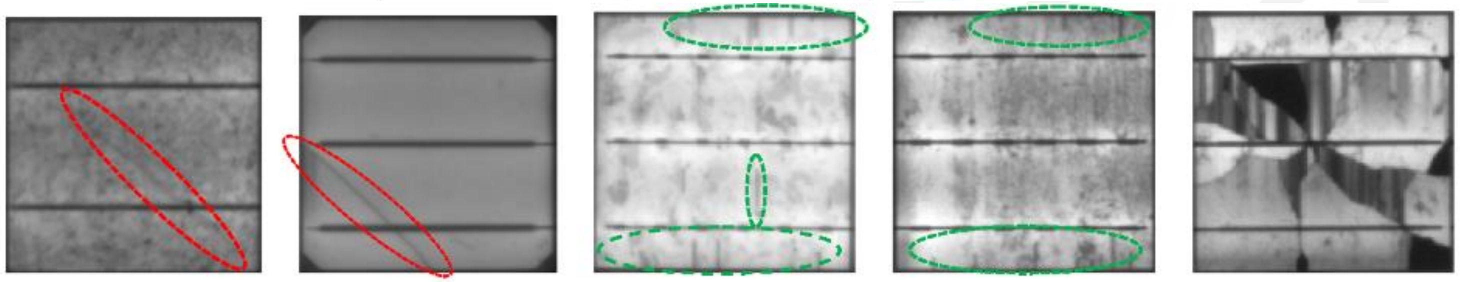
Fault detection procedure by CNN, EL images.
Dataset: 2150 EL images.
Accuracy: 82%.





Dataset (consisting of four types of defect conditions)	Dataset size (number of EL images)
Training set	1600 × 4 × 4
Validation set	400 × 4 × 4
Test set	150 × 4

Architecture of CNN based model for defect classification.



-Tang W, Yang Q, Xiong K, Yan W. Deep learning based automatic defect identification of photovoltaic module using electroluminescence images. Sol Energy 2020;201:453–60.

-Su B, Chen H, Zhou Z. BAF-Detector: An Efficient CNN-Based Detector for Photovoltaic Cell Defect Detection. IEEE Trans Ind Electron 2021.

Summary & Take-Home Messages

- PV systems experience various **unexpected faults** due to human errors, Temperature , Humidity , mechanical load ,UV irradiation, shading, irreversible equipment damage, and environmental impacts and so on.
- The **increasing number of PV installation** as well as related **massive volumes of data** which are collected from energy meters and sensors reveal the importance of **developing new monitoring technologies** and procedures that can handle such large volumes of systems and data.
- Recent advances in software, hardware and also platforms for **large data acquisition, storage and Big Data Analytics (BDA) aim to recognize the failures, faults and malfunctions in PV components efficiently, quickly and precisely** as well as increase the reliability and durability of PV systems.
- The **artificial intelligence techniques** (ML/DL) aim to detect and classify any failures in PV systems accurately and authomatically.
- To improve the accuracy of faults detection in PV system by ML/DL techniques, a **large dataset required** (from the field and or lab via failure detection methods) for the **learning and training process**.
- Various ML/DL methods like **Probabilistic Neural Network, Random Forest Learning, Conventional Neural network (CNN), decision tree (DT), Kernel-based Extreme Learning Machine (KELM), Graph-Based Semi-Supervised Learning (GBSSL), Support Vector Machine (SVM) etc**. were used for faults diagnosis in PV systems.
- **Optimization methods** (e.g. **Genetic Algorithm, Grid Search** and etc.) are used for **parameters optimization** of the **classifiers** and **feature selection** in order to obtain a higher performance in diagnosing the faults in PV systems.

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