

# Reliable diagnostic?



# EAGLE PROJECT

AI-driven Defect Detection in Solar Panels

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**FFHS**

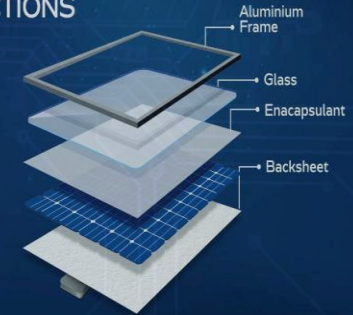
**SUPSI PVLab Team**

Ebrar Özkalay  
Mauro Caccivio

# Multi-Spectral Imaging



HOW SOLAR PANEL  
IS MADE?  
SOLAR COMPONENTS  
AND FUNCTIONS



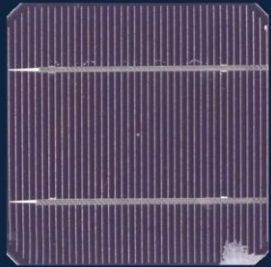
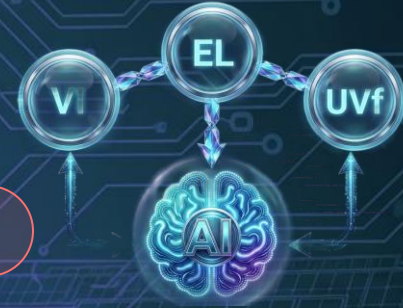
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# Our Innovative Approach

## Multispectra Defect Detection

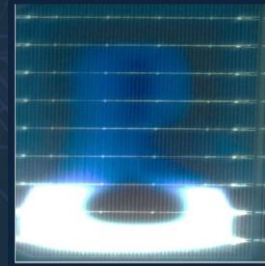
Crack • Dark Spots • Corrosion • Delamination • Discoloration



Visible (VI)



Electroluminescence (EL)



UV Fluorescence (UVf)

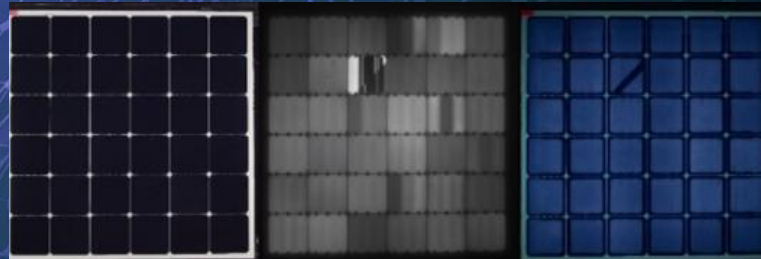
# Our Data

TISO modules mono-c-Si



## Cell Technologies:

Heterojunction, PERC, TOPCON, Back Contact



## Measurement Details:

IV measurement by PVLab in SUPSI - open circuit voltage

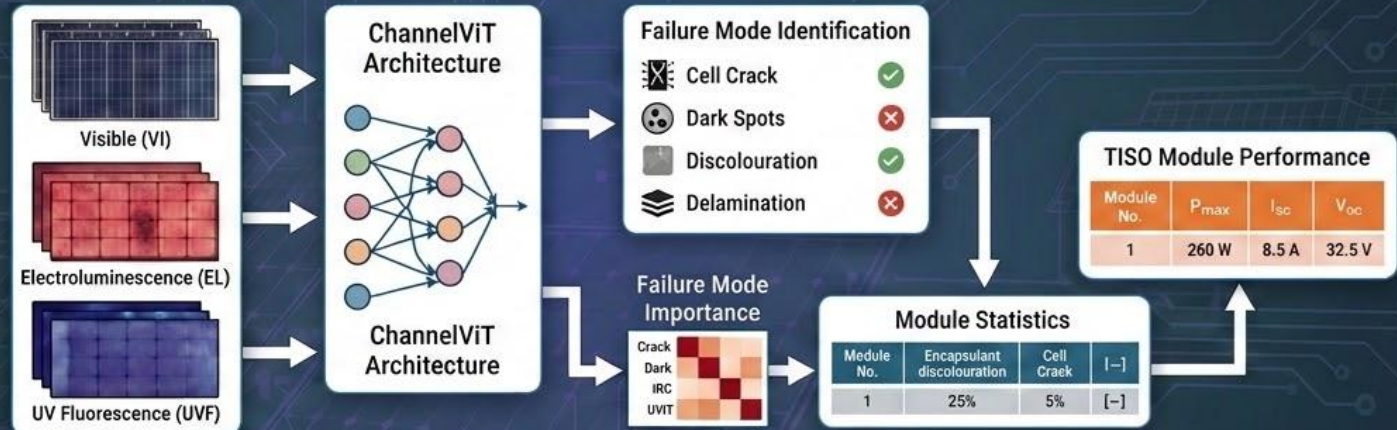
# Mission 1: Automatic identification of defects



|      |         |               |      |      |      |      |      |         |         |
|------|---------|---------------|------|------|------|------|------|---------|---------|
| good | good    | cracked       | good | good | good | good | good | cracked | cracked |
| good | cracked | Expert needed | good | good | good | good | good | cracked | good    |
| good | good    | good          | good | good | good | good | good | good    | good    |
| good | good    | good          | good | good | good | good | good | good    | good    |

Good Cracked Expert needed

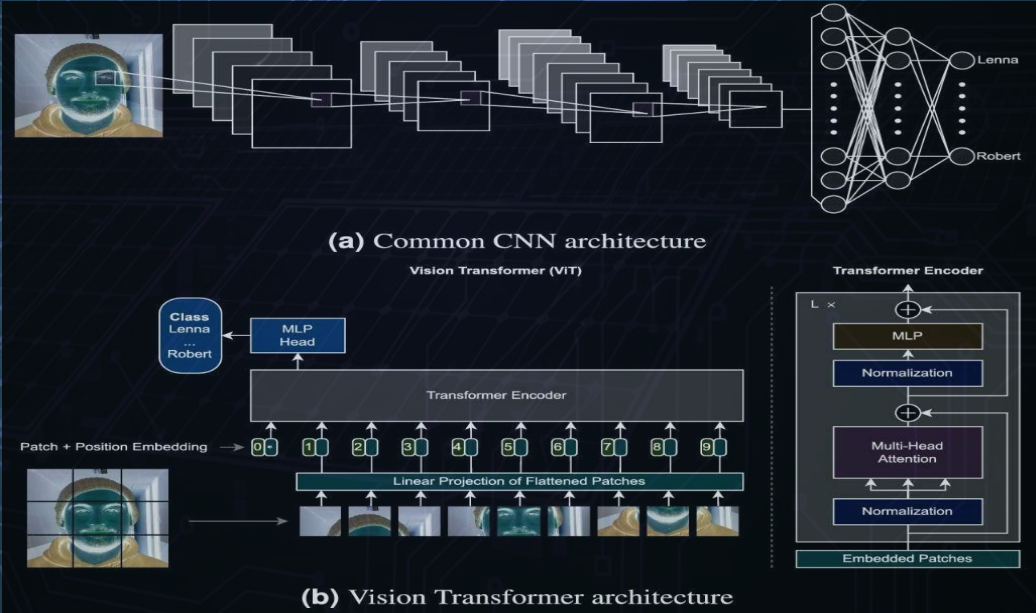
# Mission 2: Correlate it with performance



- Identify and quantify "failure modes" (defects) across multiple visual channels.
- Correlate defects directly with measurable performance loss in TISO modules.

# ViT vs. CNN

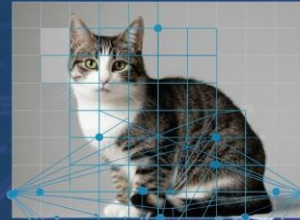
## Comparing Architectural Paradigms



# ViT vs. ChannelViT

Comparing Standard and Multi-Channel Architectures

## Vision Transformer (ViT)

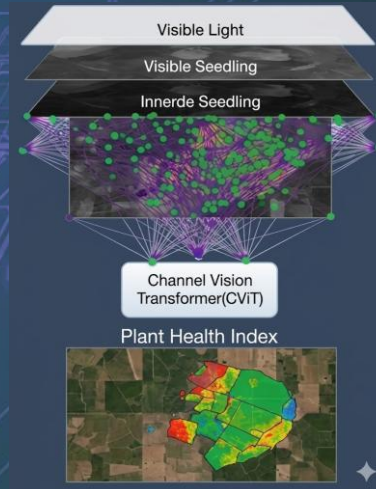


Vision Transformer  
(ViT)

Cat

VS

## Channel ViT



Processes single-stream visual input

Integrates multi-channel (VI, EL, UVf) dependencies

# Core Technology

## Channel Vision Transformer (ChannelViT)



### Multi-Channel Complexity

"Sees" across channels—intelligently combining and interpreting information from *all five image channels* (VI, EL, UVf).



### Precise Defect Detection

Leverages complex dependencies between channels for superior detection accuracy.

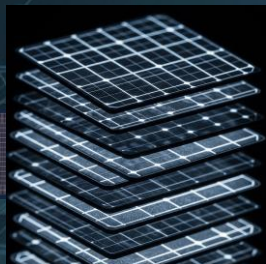


### Channel Availability

Scalable framework designed for high-throughput image processing environments.

# LLM-Assisted Pre-labeling

## Raw Images



Thousands of images

## LLM Pre-labeling (Proposals)



**LLM Analysis**  
Extracting patterns across  
images

## Pre-labeled Output



## Important Distinction

We do **NOT** use the LLM  
to **replace** the final model.

**LLM**  
Generalist



**ChannelViT**  
Specialist

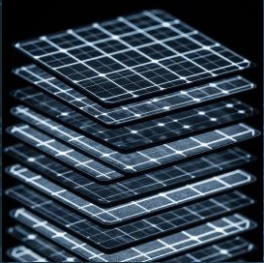


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The LLM handles the  
**'grunt work'** of initial  
organization, but the  
heavy lifting of high-precision  
diagnostic remains with our  
properly trained, **domain-  
specific models**.

# THE HUMAN-IN-THE-LOOP WORKFLOW

## Raw Images



Thousands of Unlabeled Images

## LLM Pre-labeling (Proposals)



- Finger Break
- PID / Micro Crack
- Inactive Area
- Hotspot

## Human Expert Review (Ground Truth)



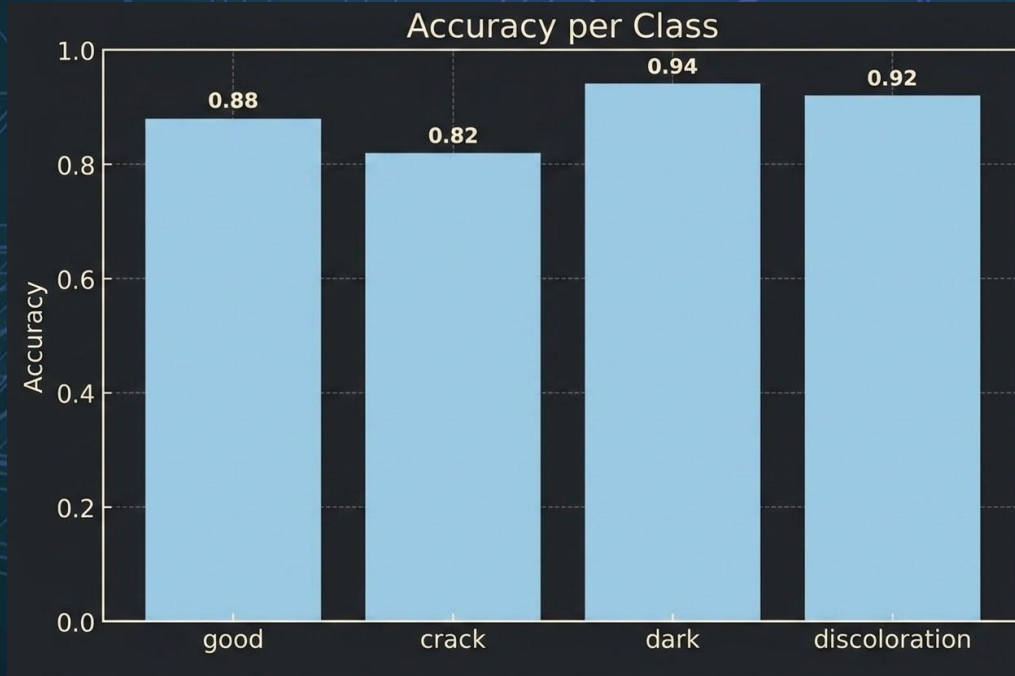
Expert validates, corrects edge cases, and verifies complex defect overlaps.

## Train Specialist Model (EAGLE / ChannelViT)



Trained on 100% high-quality data for high-precision diagnostics.

# Efficiency of the defect classification model



## Key Metrics

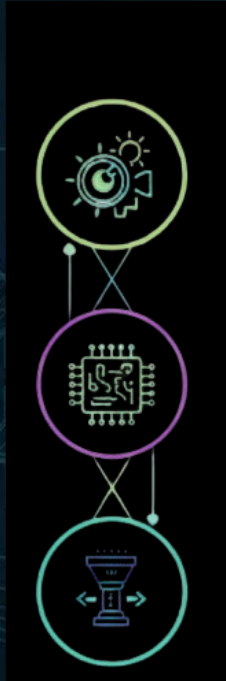
Avg. Accuracy:  
**89%**

Best Class: **Dark**  
(94%)

Lowest Class:  
**Crack** (82%)

The model shows high consistency across diverse defect types, with particularly strong performance in identifying dark spots.

# Performance Prediction



## Multispectral

| Metric               | ResNet-18 |
|----------------------|-----------|
| MAE                  | 4.35      |
| MedAE                | 3.38      |
| MSE                  | 32.79     |
| R <sup>2</sup> Score | 0.47      |

## Only EL

| Metric               | ResNet-18 |
|----------------------|-----------|
| MAE                  | 5.67      |
| MedAE                | 4.72      |
| MSE                  | 50.61     |
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A separate machine learning model predicts electrical performance metrics (Max. Power, Short-Circuit Current, Open-Circuit Voltage) directly from the multispectral images.

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# FUTURE

## Validating & On-site Drone Analysis



Validating in controlled environment,  
future - on-site drone analysis.

## Advanced Measurements & Digital Twins

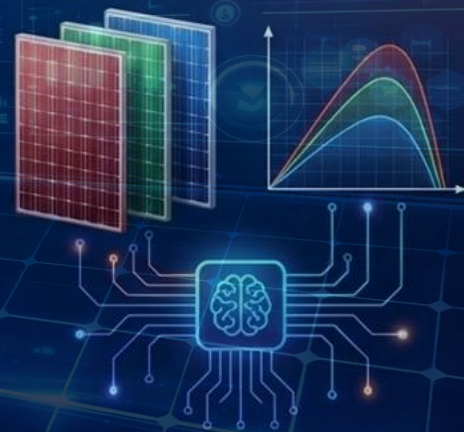


Other type of measurements:  
Thermography, Daylight  
electroluminescence integration.



Digital twins.

## Power to Image & Colored PVs



Power to Image correlation – for  
colored PV panels.

# Contact us!

## FFHS

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