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An assessment of the value of **principal component analysis** for photovoltaic IV trace classification of **physically-induced failures**

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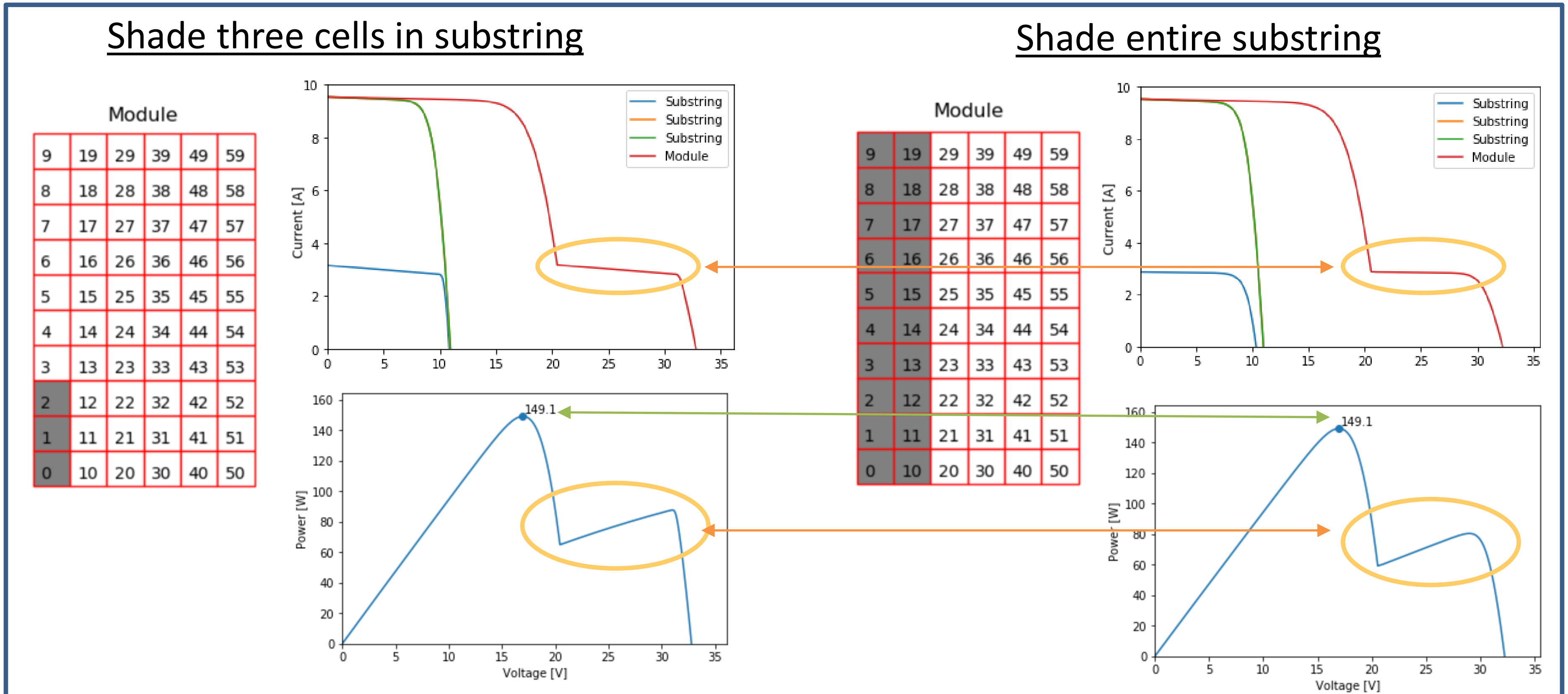
Background and Motivation

- **Improved diagnostics** for PV failures are ***critical* for ensuring reliability**
- IV traces are a common technique used to evaluate string or module performance
- IV traces have been classified by feature extraction (I_{sc},V_{oc},FF, R_{SH}, R_s, etc.), **but some failure characteristics *may* be missed.** For example,



Shaded irradiance = 300 W/m2, Other cells at 1000 W/m^2

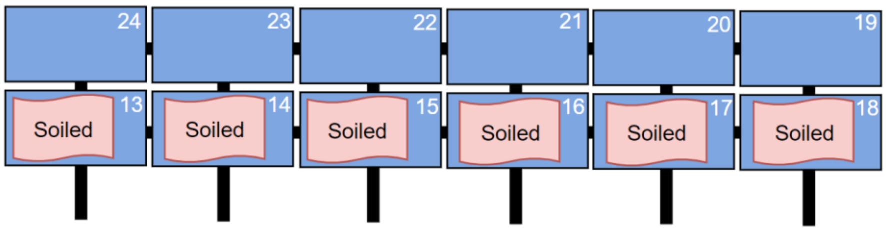
Plots courtesy of Josh Stein, Sandia National Labs

- **Principal component analysis** improves feature variance, and has shown success in IV classification [1]

Physical implementation of failure modes

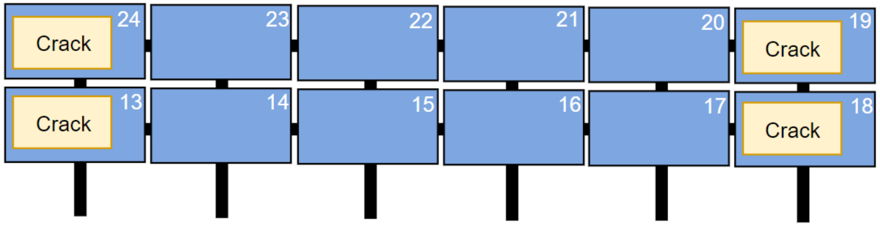
- Located at Florida Solar Energy Center (FSEC) in Cocoa, Florida
- A control string and a test string are implemented with 12 modules each
- The test string has three modes: *unstressed*, *partial soiling*, and *cell cracking*

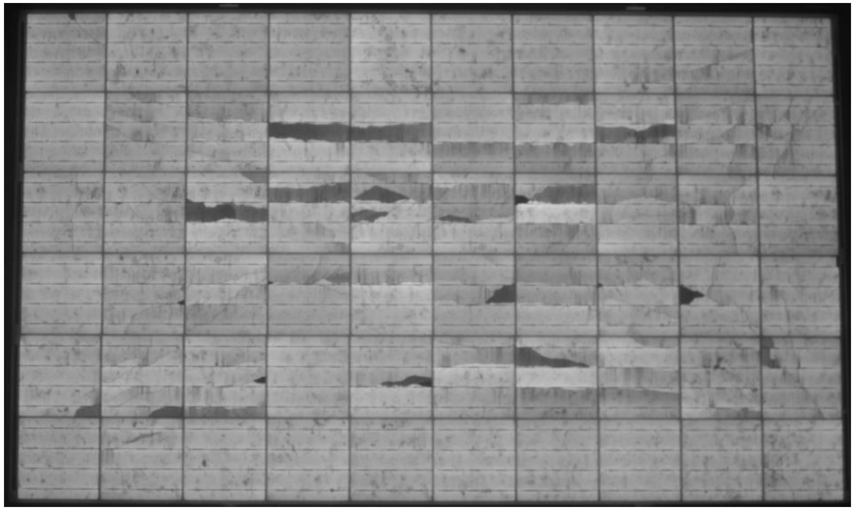
Partial Soiling



- Semi-transparent polymer film was laid on top of the bottom six modules [2]

Cell Cracking

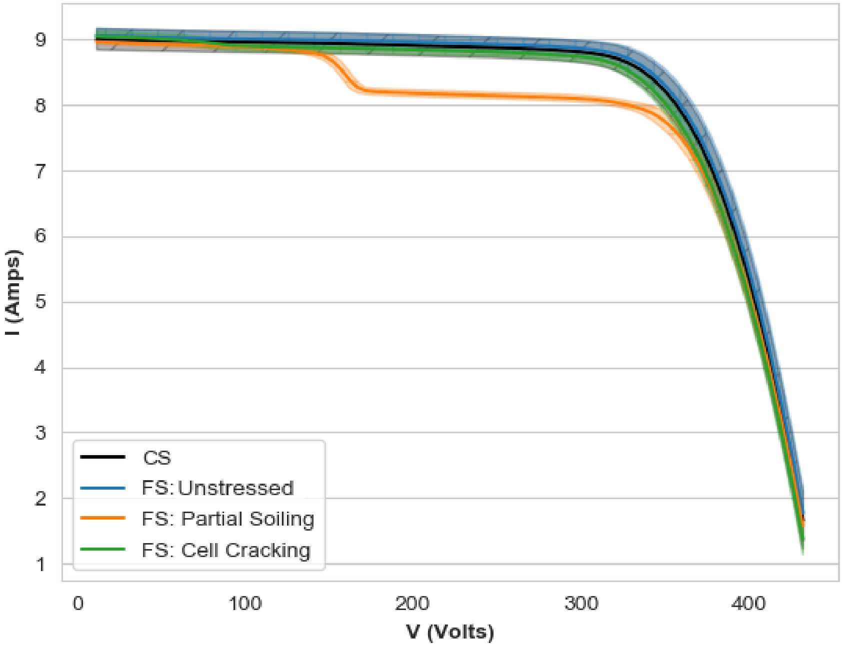




- Modules underwent a sequence of increasingly damaging thermomechanical loads [3,4]

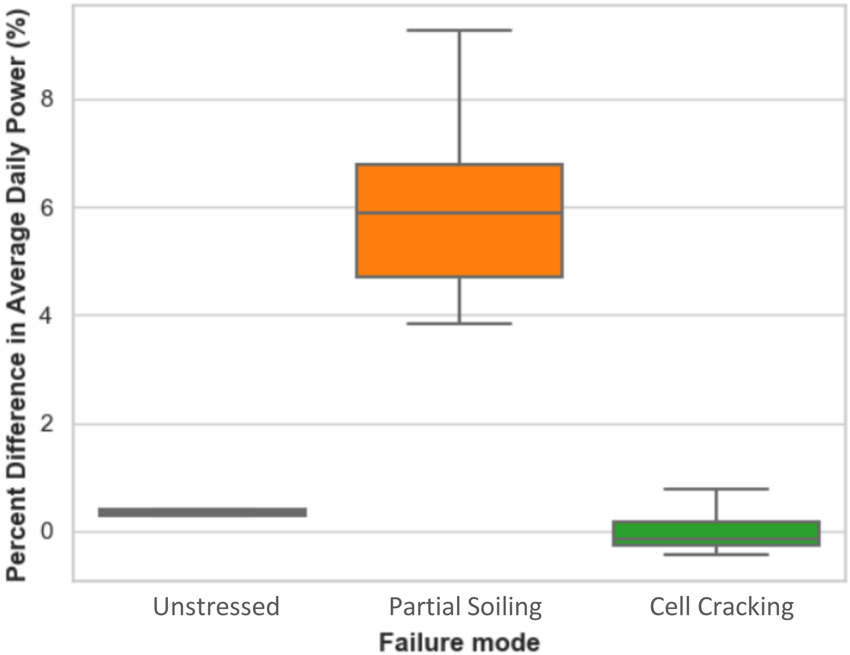
Methodology: First looks at the data

Average IV curve per mode



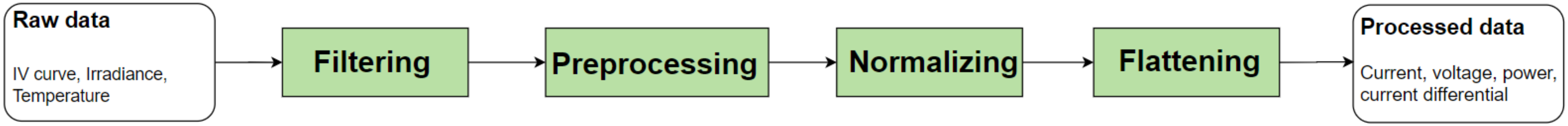
Average IV curve profiles for control string (CS), and three modes in the faulted string (FS) shows identifiable trends in each failure mode. A standard deviation region is included on all samples.

Percent difference in average daily power per mode

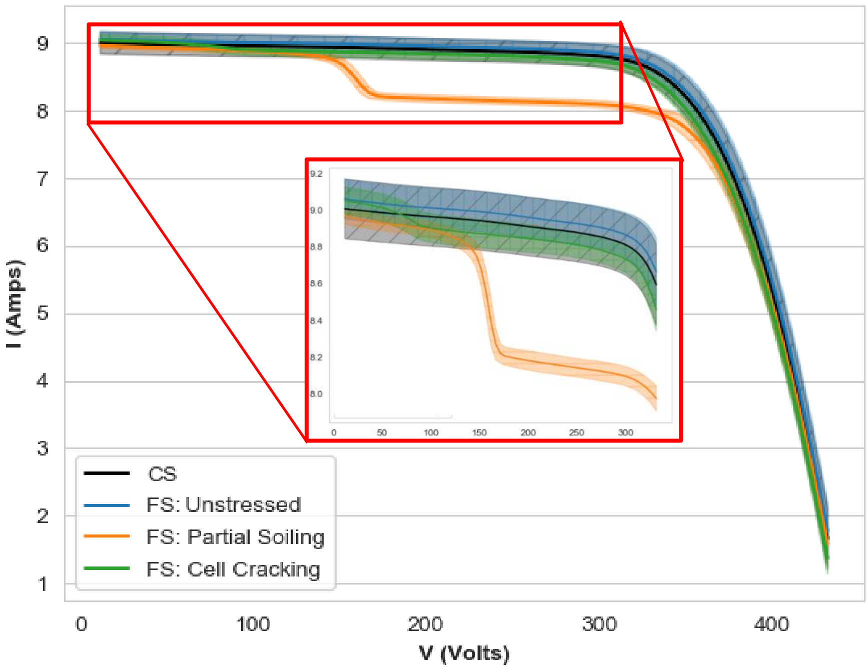


Max power point tracking (MPPT) data shows large power loss in partial soiling failure but relatively small, sometimes undetectable, loss in cell cracking failure

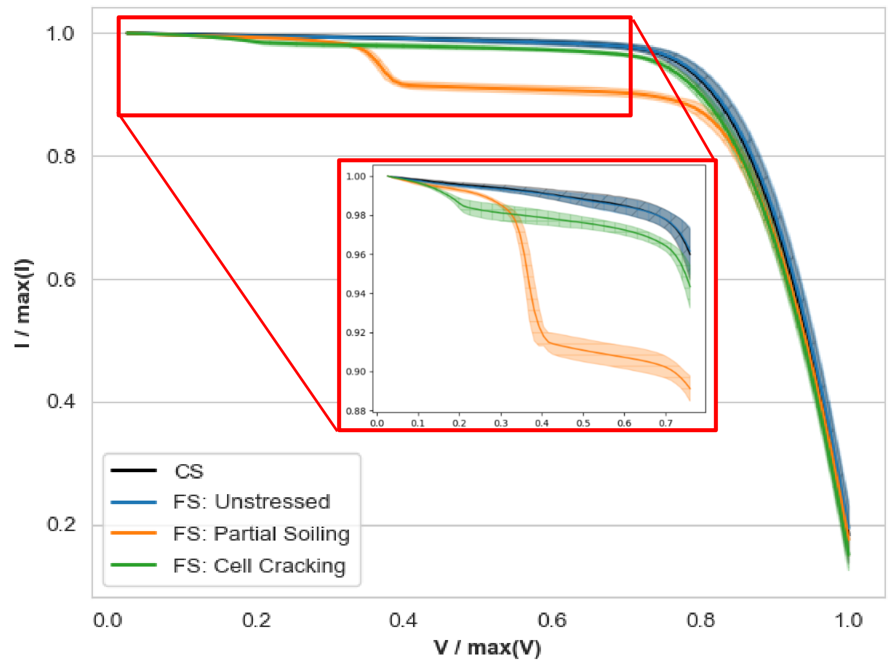
Methodology: Data filtering and processing



Preprocessed



Preprocessed & Normalized



Methodology: Feature calculation and data flattening

Raw data (IV curve, Irradiance, Temperature) → **Filtering** → **Preprocessing** → **Normalizing** → **Flattening** → **Processed data** (Current, voltage, power, current differential)

Feature calculation

Power: product of current and voltage

Current "Differential": is evaluated as the consecutive, pairwise differences in the current

$$D = \{0, (I_1 - I_0), ..., (I_m - I_{m-1})\}$$

Flattening

"Trace-level"

Datetime	IV Voltage	IV Current	IV Power	Differential $D = (I_{n,m} - I_{n,m-1})$	y
3/1/2020 08:00:00	$[V_{0,0}, V_{0,1}, \ldots, V_{0,m}]$	$[I_{0,0}, I_{0,1}, \ldots, I_{0,m}]$	$[P_{0,0}, P_{0,1}, \ldots, P_{0,m}]$	$[0, D_{0,1}, \ldots, D_{0,m}]$	0
3/1/2020 08:30:00	$[V_{1,0}, V_{1,1}, \ldots, V_{1,m}]$	$[I_{1,0}, I_{1,1}, \ldots, I_{1,m}]$	$[P_{1,0}, P_{1,1}, \ldots, P_{1,m}]$	$[0, D_{1,1}, \ldots, D_{1,m}]$	0
...	$[V_{n,0}, V_{n,1}, \ldots, V_{n,m}]$	$[I_{n,0}, I_{n,1}, \ldots, I_{n,m}]$	$[P_{n,0}, P_{n,1}, \ldots, P_{n,m}]$	$[0, D_{n,1}, \ldots, D_{n,m}]$	k

→

"Point-level"

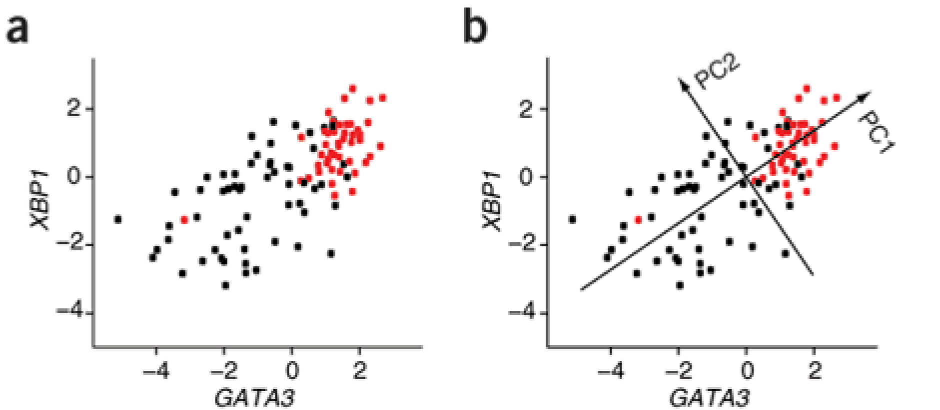
IV Voltage	IV Current	IV Power	Differential	y
$V_{0,0}$	$I_{0,0}$	$P_{0,0}$	$D_{0,0}$	0
$V_{0,1}$	$I_{0,1}$	$P_{0,1}$	$D_{0,1}$	0
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$V_{0,m}$	$I_{0,m}$	$P_{0,m}$	$D_{0,m}$	0
$V_{1,0}$	$I_{1,0}$	$P_{1,0}$	$D_{1,0}$	0
$V_{1,1}$	$I_{1,1}$	$P_{1,1}$	$D_{1,1}$	0
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$V_{1,m}$	$I_{1,m}$	$P_{1,m}$	$D_{1,m}$	0
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$V_{n,m}$	$I_{n,m}$	$P_{n,m}$	$D_{n,m}$	k

For *n* samples across *k* failure modes with *m* IV points

Adapted from Fadhel et al [1]

Brief overview of ML techniques

Principal Component Analysis (PCA)



Principal components are evaluated as linear combinations of the input variables, constituting new axis in the input feature space. Figure from [5]

Flattened data

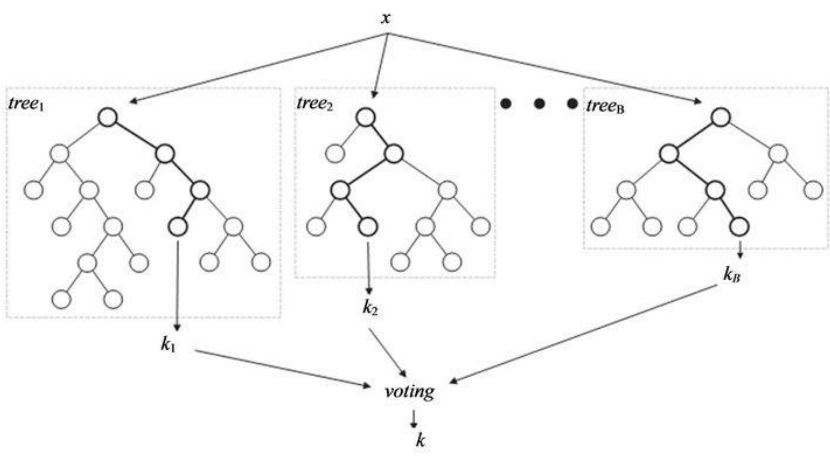
IV Voltage	IV Current	IV Power	Differential
$V_{0,0}$	$I_{0,0}$	$P_{0,0}$	$D_{0,0}$
$V_{0,1}$	$I_{0,1}$	$P_{0,1}$	$D_{0,1}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
$V_{0,m}$	$I_{0,m}$	$P_{0,m}$	$D_{0,m}$
$V_{1,0}$	$I_{1,0}$	$P_{1,0}$	$D_{1,0}$
$V_{1,1}$	$I_{1,1}$	$P_{1,1}$	$D_{1,1}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
$V_{1,m}$	$I_{1,m}$	$P_{1,m}$	$D_{1,m}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
$V_{n,m}$	$I_{n,m}$	$P_{n,m}$	$D_{n,m}$

PCA →

Transformed data

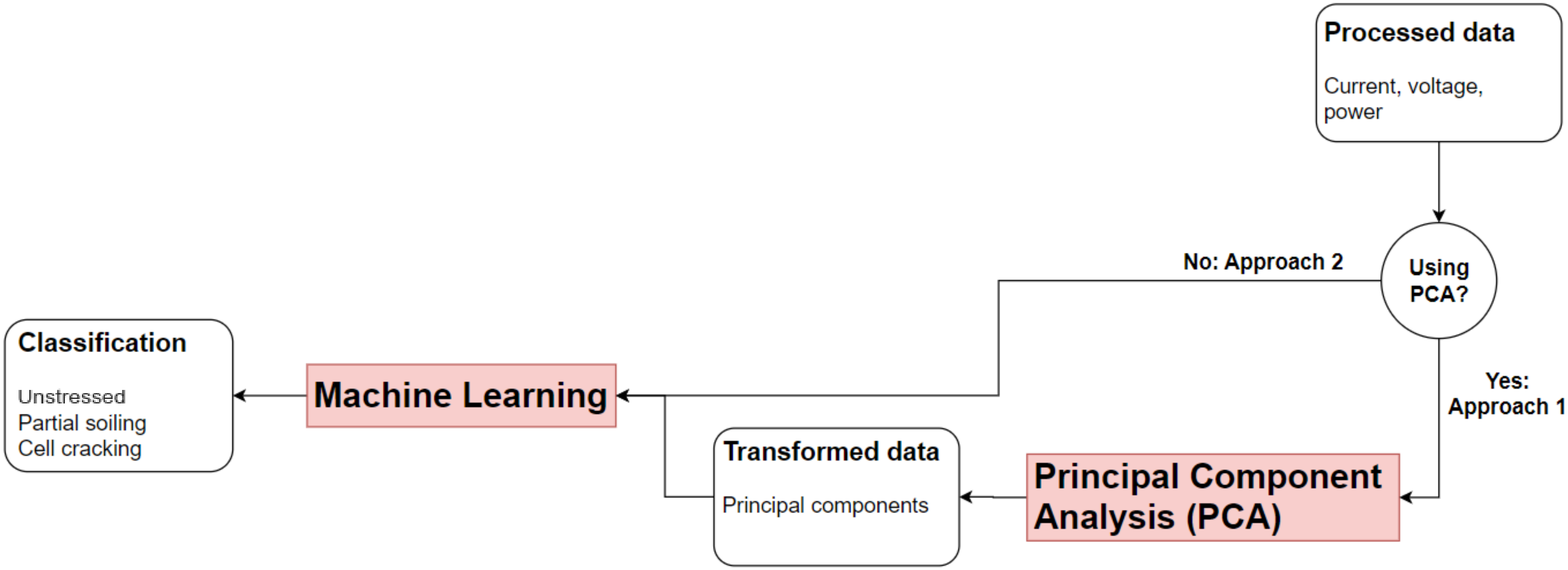
PC1	PC2	PC3
$PC1_1$	$PC2_1$	$PC3_1$
$PC1_2$	$PC2_2$	$PC3_2$
$\vdots$	$\vdots$	$\vdots$
$PC1_{n*m}$	$PC2_{n*m}$	$PC3_{n*m}$

Random Forest (RF)



Random Forest (RF) is an *ensemble of decision trees*. Figure from [6]

Methodology: Feature reduction and classification

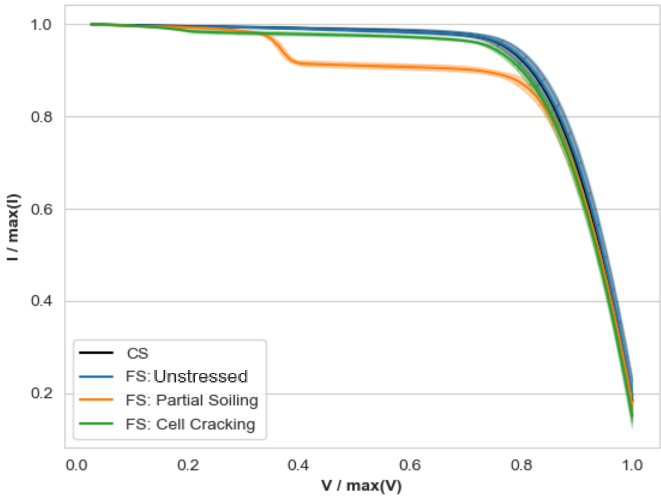


Two approaches are studied:

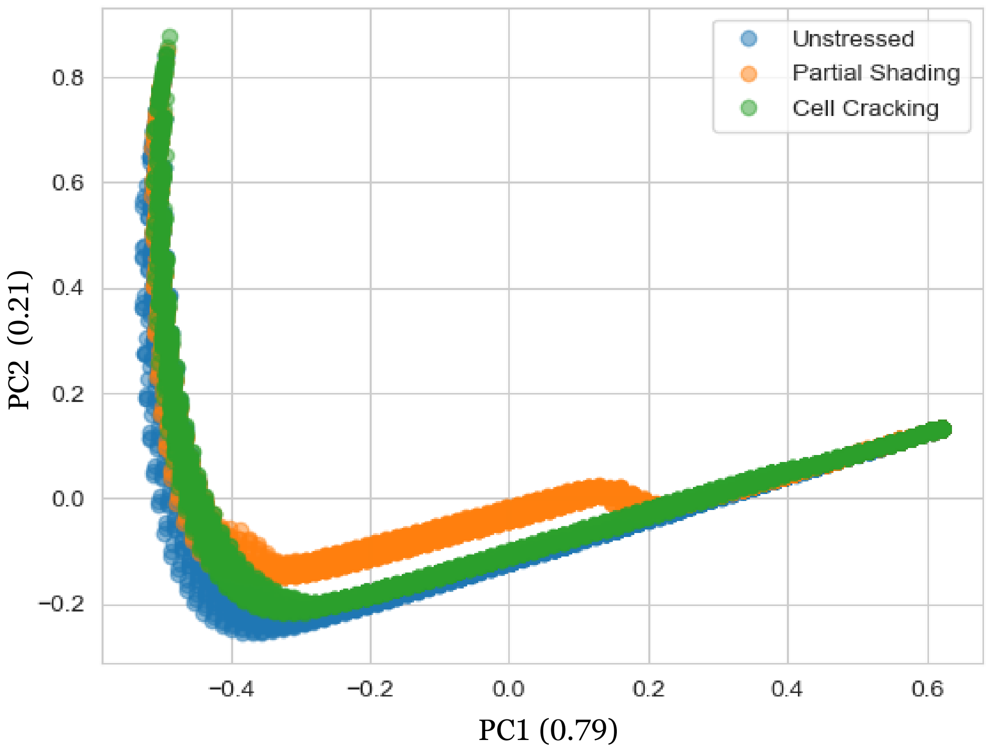
1. With PCA: Conduct PCA on input features, push principal components into machine learning model
2. Without PCA: Push input features into machine learning model

Results: PCA has minimal effect on the feature space

Processed and Corrected IV curves



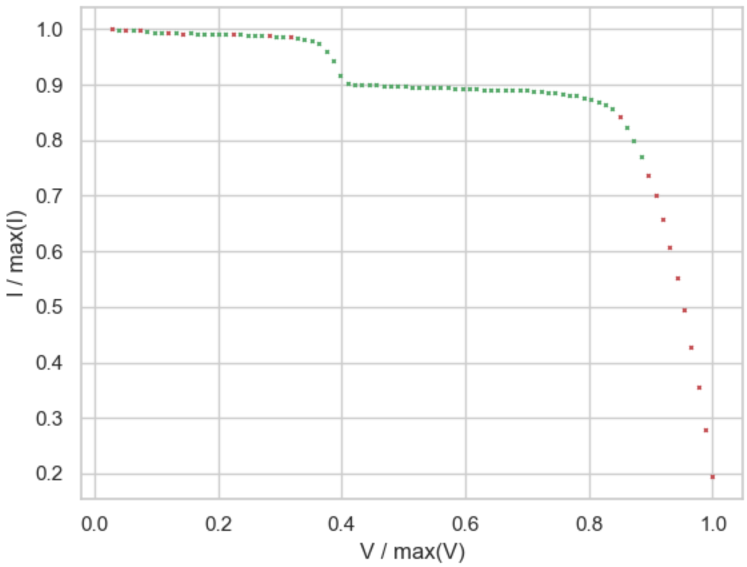
PCA Space



- The PCA space looks like the IV curve data except rotated
- The vertical portion of the curve shows higher differentiation than the IV curve due to the Differential parameter

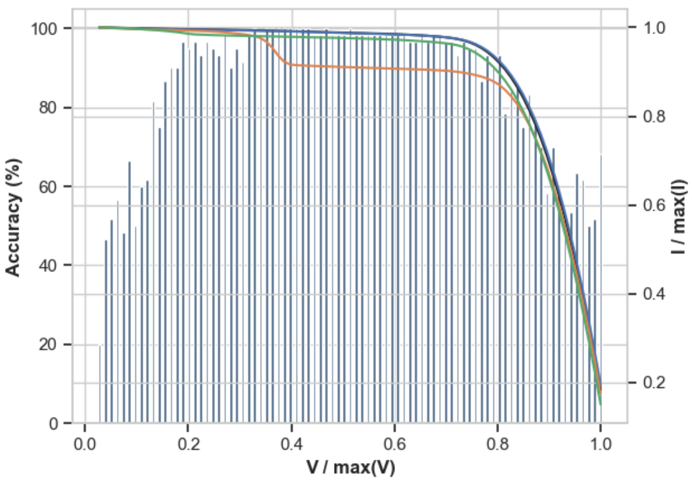
Results: Accuracy profiles

Example: “Partial Soiling” IV Profile

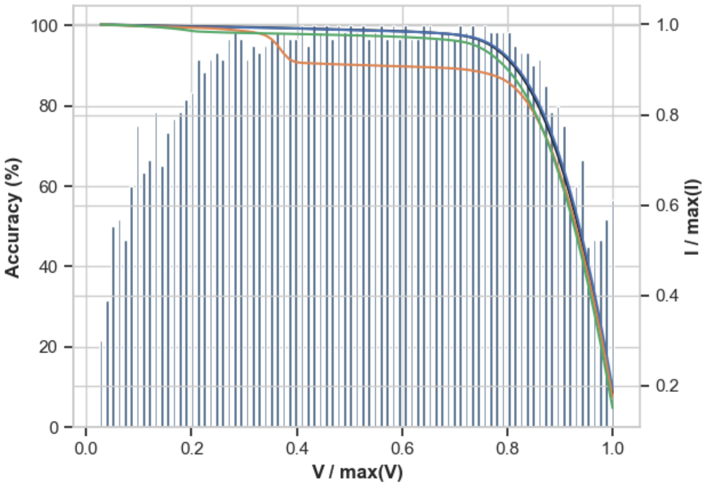


The majority of points (77%) classified correctly (green) as a partial soiling. Because this is the majority, the ‘trace’ is classified as a partial soiling.

With PCA



Without PCA



- **Higher accuracies** located where failure modes *visually differentiate*
- Similar accuracy profiles are seen on both With/Without PCA

Results: Accuracy evaluations

Tactic	Average accuracy (std. dev.) over 20 tests							
	Point-level				Trace-level			
	Unstressed	Partial soiling	Cell cracking	Total	Unstressed	Partial soiling	Cell cracking	Total
With PCA	84.2 (2.7)	77.5 (1.4)	78.7 (1.8)	80.2 (0.9)	99.1 (2.0)	1.0 (0)	1.0 (0)	**99.5 (0.8)**
Without PCA	84.3 (2.4)	85.6 (1.5)	84.7 (1.7)	85.1 (1.0)	96.7 (2.4)	1.0 (0)	99.8 (1.1)	**98.3 (1.3)**

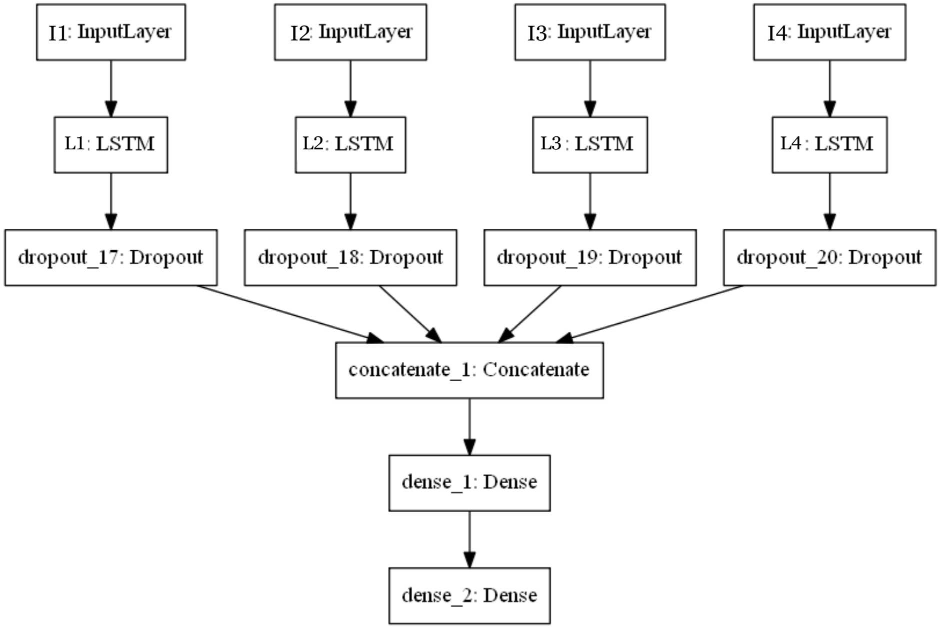
- Average accuracy is higher on trace-level than point-level
- At the trace-level evaluation, PCA is shown to improve results from 98.3% to 99.5% on average, mostly attributed to the notable improvement in the classification of unstressed curves.
- While the implementation using PCA performs better on the trace-level, it has a lower performance on the point-level. This means that the “Without PCA” implementation has higher accuracies, but when conglomerating them into traces, the misclassifications are likely grouped more often and thus performs worse at a trace level.

Conclusion

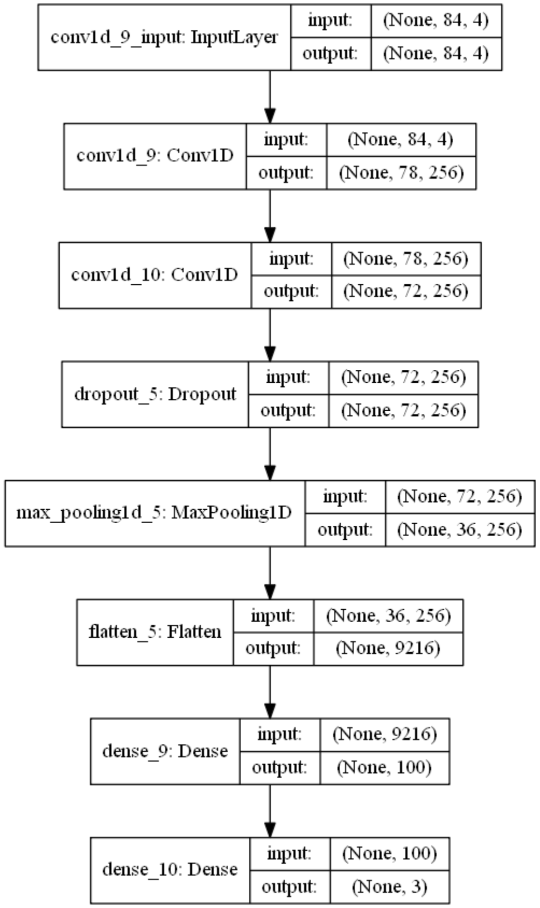
- In our case, PCA gives marginal improvement in accuracy (+1.2%, on average)
- High accuracies (>98%) are found *even though* we incorporate failure modes which minorly affect the IV curve
- Preprocessing steps are essential towards differentiating our failure modes
- Model deployment is running successfully with similar accuracies

Future work: IV pattern recognition with neural networks

Multi-headed LSTM Architecture



1D CNN Architecture



Why neural networks?

- Could scale well with more failure modes which have less variability

References

[1] Fadhel, S., et al. "PV shading fault detection and classification based on IV curve using principal component analysis: Application to isolated PV system." *Solar Energy* 179 (2019): 1-10.

[2] Walters, Joseph, H. Seigneur, E. Schneller, M. Matam and M. Hopwood, "Experimental Methods to Replicate Power Loss of PV Modules in the Field for the Purpose of Fault Detection Algorithm Development," *2019 IEEE 46th Photovoltaic Specialists Conference (PVSC)*, Chicago, IL, USA, 2019, pp. 1410-1413, doi: 10.1109/PVSC40753.2019.8980896.

[3] Rowell, Michael W., et al. "The effect of laminate construction and temperature cycling on the fracture strength and performance of encapsulated solar cells." *2018 IEEE 7th World Conference on Photovoltaic Energy Conversion (WCPEC)(A Joint Conference of 45th IEEE PVSC, 28th PVSEC & 34th EU PVSEC)*. IEEE, 2018.

[4] Schneller, Eric J., et al. "The Impact of Cold Temperature Exposure in Mechanical Durability Testing of PV Modules." *2019 IEEE 46th Photovoltaic Specialists Conference (PVSC)*. IEEE, 2019.

[5] Ringnér, Markus. "What is principal component analysis?." *Nature biotechnology* 26.3 (2008): 303-304.

[6] Nguyen, Cuong, Yong Wang, and Ha Nam Nguyen. "Random forest classifier combined with feature selection for breast cancer diagnosis and prognostic." (2013).

Collaboration – synergy through teamwork

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Thank you!

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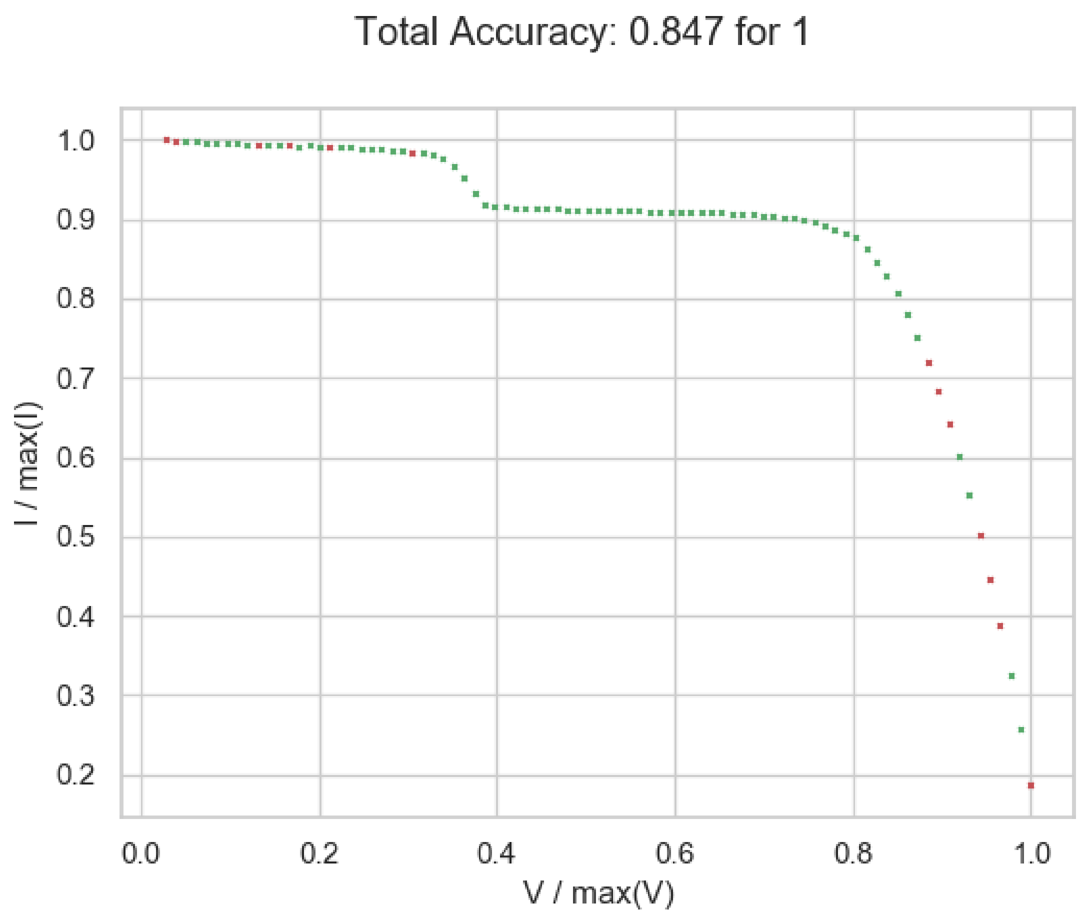
APPENDIX


Total Accuracy: 0.847 for 1
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
I / max(I)
0.0
0.2
0.4
0.6
0.8
1.0
V / max(V)

With PCA

Feature	Importance
PC1	0.499
PC2	0.501

Without PCA

Feature	Importance
Current	0.538
Power	0.320
Voltage	0.142

UCF