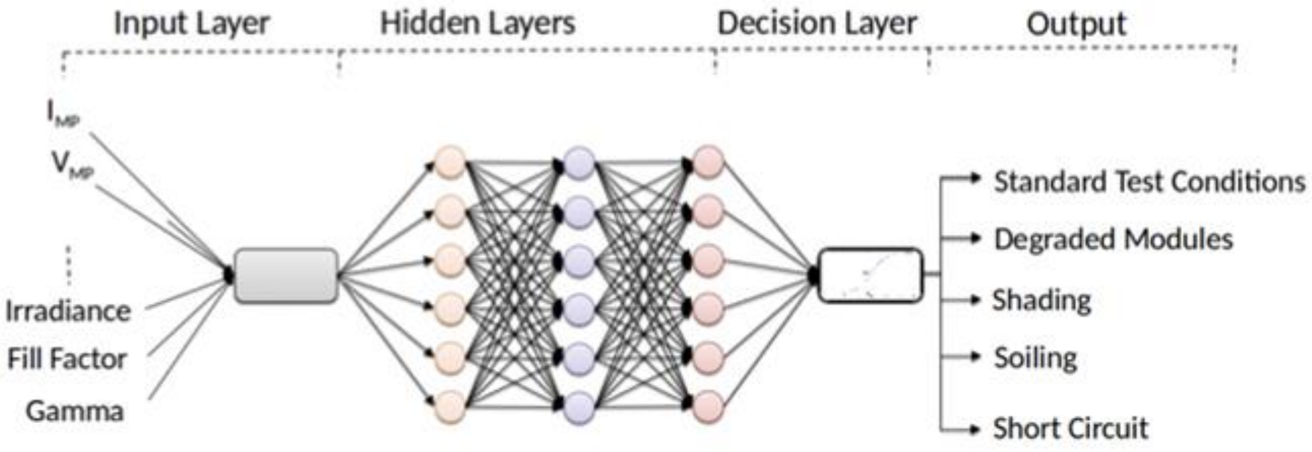
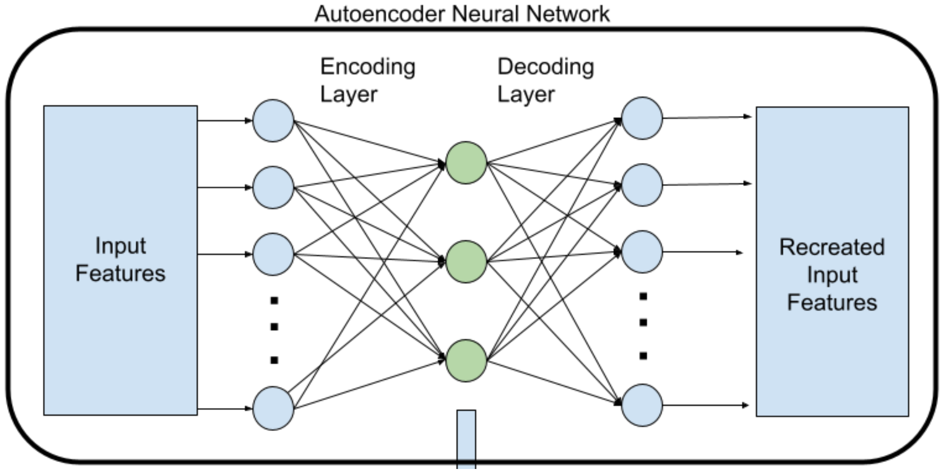
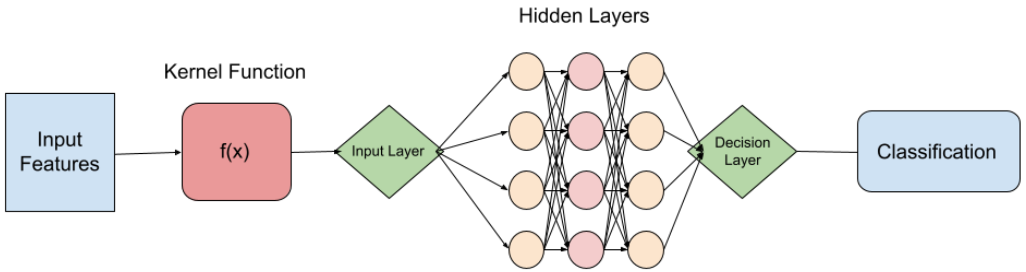
Feature Studies for PV Fault Classification Using Nonlinear Principal Component Analysis

Maxwell Yarter [1], Gowtham Muniraju [1], Andreas Spanias [1], Yiannis Tofis [2]
[1] Arizona State University School of ECEE [2] University of Cyprus KIOS Center







Ira A. Fulton Schools of Engineering
Arizona State University
University of Cyprus
Sensor Signal and Information Processing Center
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MOTIVATION

- Automatic solar fault detection is more efficient and cost effective

- Ten solar features are used for classification
  - Less features can shorten training time
  - Knowing which features are redundant informs us which sensors are needed

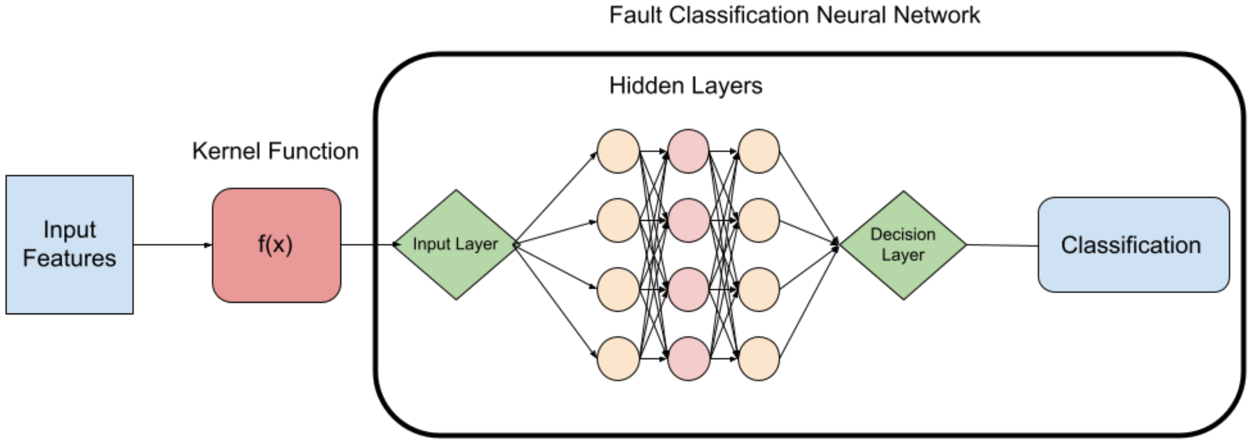
- Greater classification accuracy means more power output

PROBLEM STATEMENT AND CHALLENGES

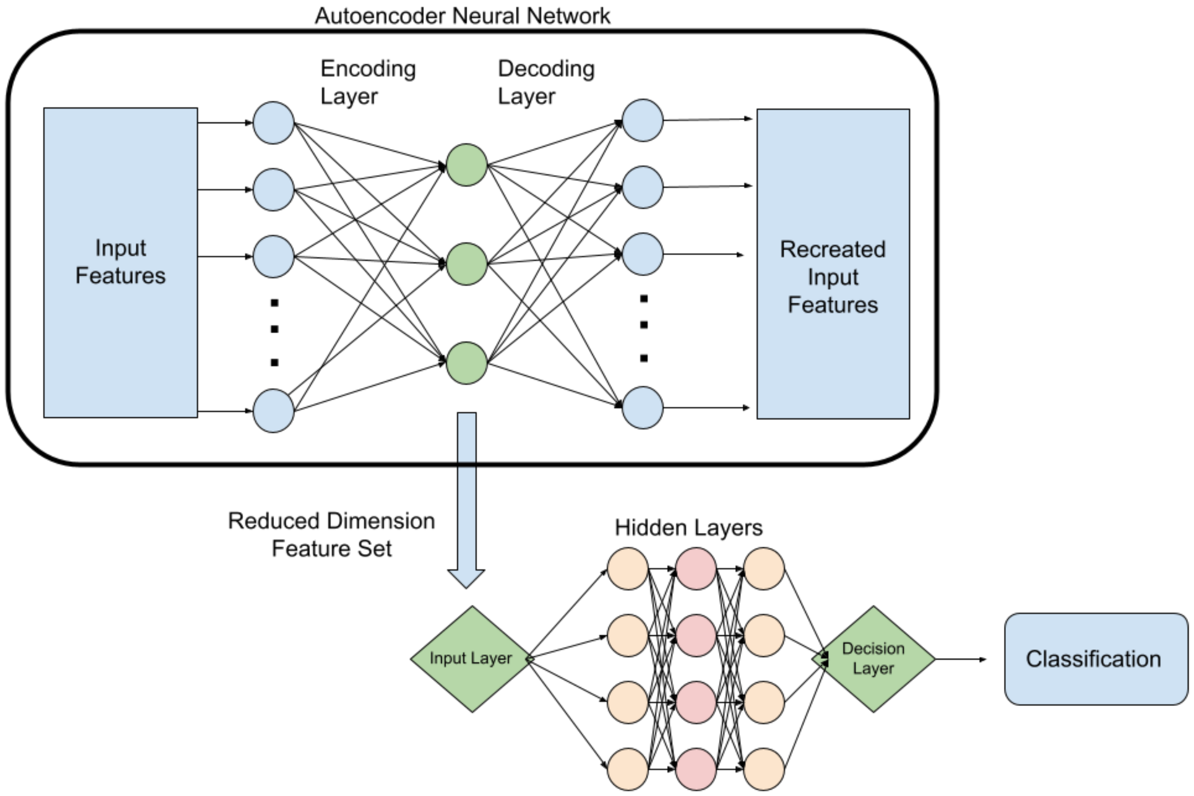
- Nonlinear PCA techniques may reduce the number of solar features needed for fault classification and improve classification accuracy.
- **Challenges:**
  - Autoencoder only eliminate redundancy and do not perfectly emulate the input data
  - Using KPCA requires training 9 different classification networks per kernel function

NONLINEAR PCA METHODS

KPCA Block Diagram



Autoencoder Block Diagram



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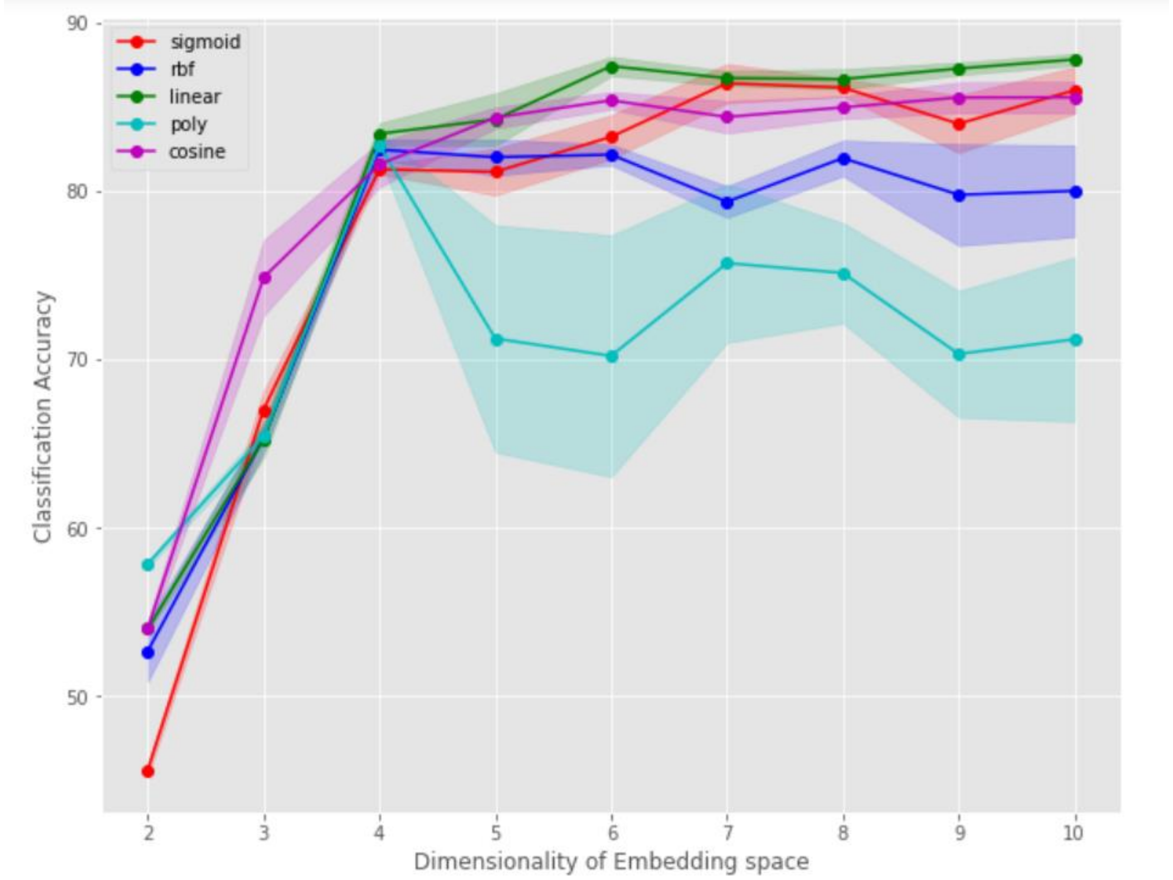
DATA SET AND KERNEL FUNCTIONS

- Data Set: NREL solar testbed 10 feature **data set [1]**
  - Features: DC Power, Max. Voltage, Max. Current, Temperature, Irradiance, Fill Factor, Gamma, Max. Power, Open Circuit Voltage, Short Circuit Current
  - Faults: Standard Test Condition, Short Circuit, Degraded, Shaded, Soiled

- Kernel Functions: linear, polynomial, RBF, sigmoid, and cosine.

RESULTS



KPCA Fault Classification Accuracy vs. Dimension of Embedding Space

	MCrun	KernelType	#2	#3	#4	#5	#6	#7	#8	#9	#10
0	0	sigmoid	45.439032	67.235494	81.585479	83.710825	83.152342	87.294447	86.472231	86.580825	86.192989
1	0	rbf	53.707725	66.025442	81.445861	82.268071	82.748991	80.359912	81.368291	83.803910	77.040023
2	0	linear	53.971457	65.715170	83.834934	85.107040	86.348122	86.053365	86.348122	87.806392	87.604713
3	0	poly	57.617128	65.110147	83.121318	75.736892	72.354949	68.864411	71.827489	71.998137	77.924293
4	0	cosine	54.576480	75.969595	80.204779	84.657151	85.013962	82.764506	86.115420	85.479367	84.517533

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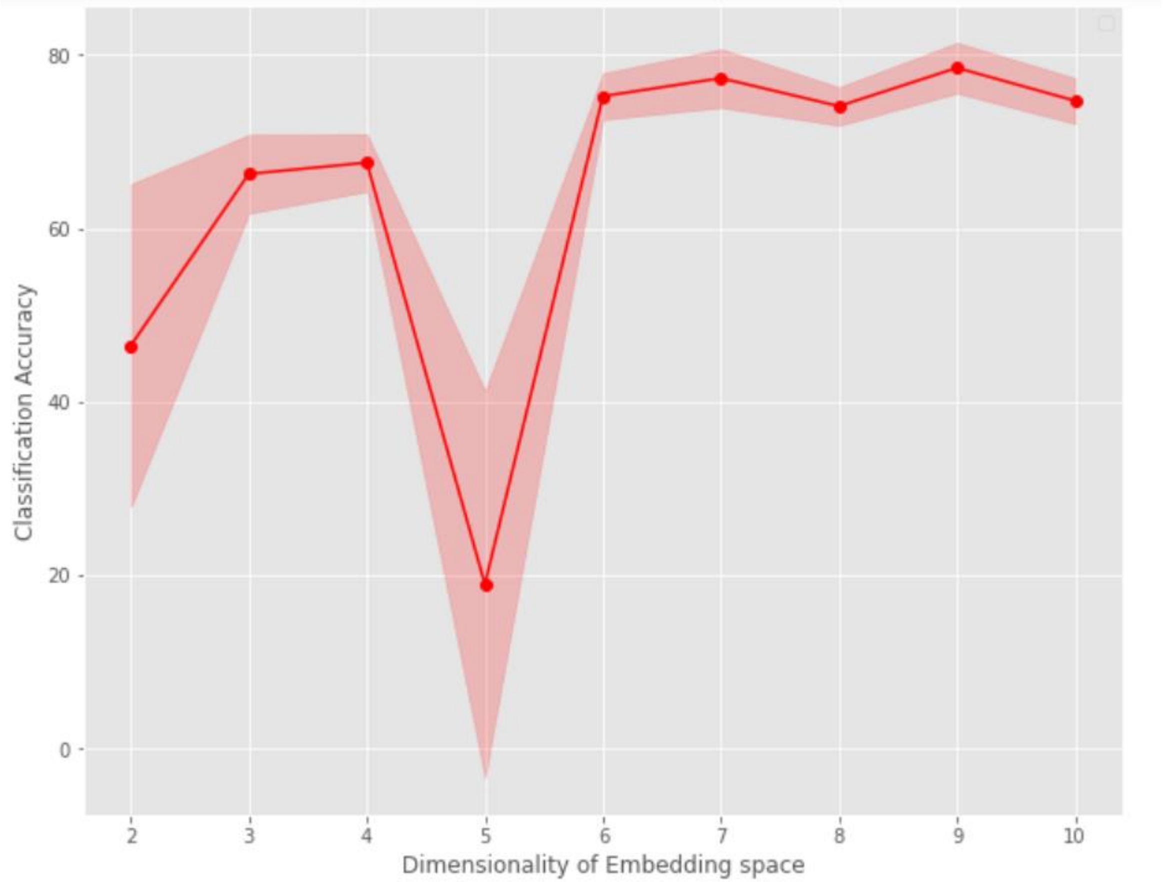
AUTOENCODER RESULTS



Autoencoder Fault Classification Accuracy vs. Dimension of Embedding Space

	MCrun	#2	#3	#4	#5	#6	#7	#8	#9	#10
0	0.0	46.493950	66.289175	67.592305	18.957493	75.255972	77.334779	74.107975	78.529322	74.728513
1	1.0	60.114801	70.415759	59.432209	77.986348	72.184300	80.096185	72.354949	80.515051	77.226186
2	2.0	19.360843	63.403660	60.843933	72.323924	67.219979	69.950354	71.393114	72.572136	79.103321
3	3.0	61.340368	62.224632	67.018306	74.681973	72.091222	74.868137	75.054300	76.140243	72.122246
4	4.0	19.484952	56.670803	62.007445	73.487437	73.611540	74.154514	77.738130	80.065155	78.793049

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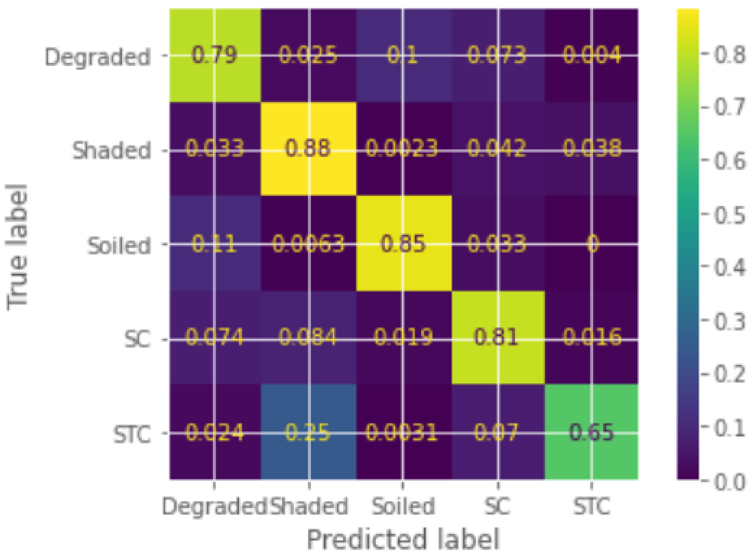
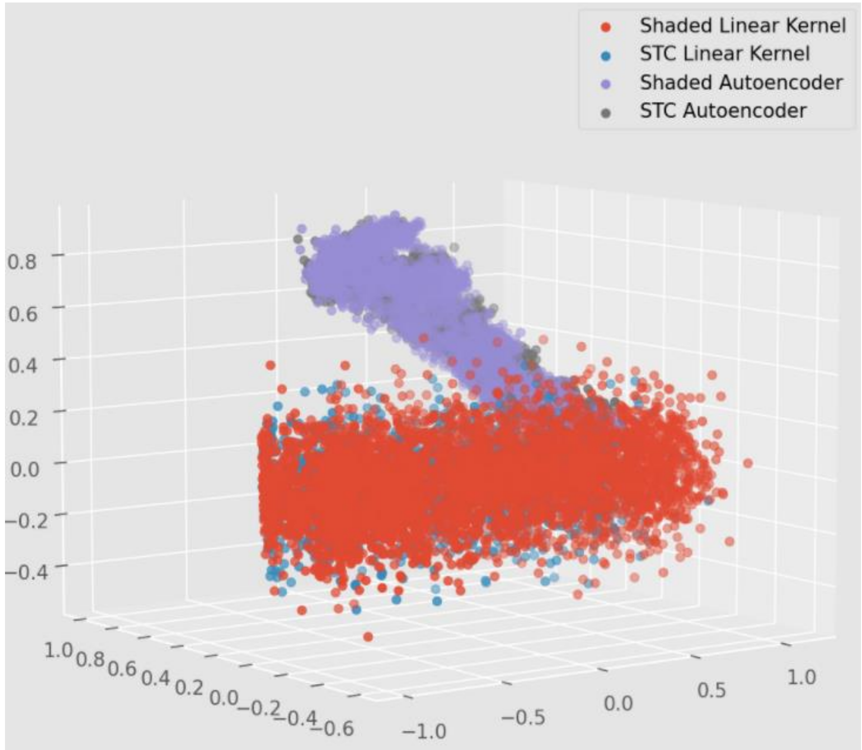
FEATURE VISUALIZATION

- Overlap in STC and Shaded feature clusters for both nonlinear techniques
- Confusion matrix shows STC and shaded misclassification



5 Feature Linear KPCA Confusion Matrix



3D Feature Space Shaded and STC Faults

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CONCLUSION

- Successful reduction of feature space
- 85.1% Accuracy using linear kernel and 5 features.
- Autoencoder <80% accuracy for all dimensions
- No nonlinear redundancy in the feature set

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ONGOING & PLANNED WORK

- Determine a feature that could distinguish between STC and shaded fault
- Verify these results using more data
- Complete IEEE format report detailing results
- Consolidate nonlinear and linear PCA results into a single paper

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