Feature Studies for PV Fault Classification Using Nonlinear Principal Component Analysis

SenSIP Algorithms and Devices IRES

Maxwell Yarter, IRES Student, Arizona State University
Graduate Mentor: Gowtham Muniraju, Faculty Advisor: Andreas Spanias, Yiannis Tofis
SenSIP Center, School of ECEE, Arizona State University

SenSIP INDUSTRY CONSORTIUM

ABSTRACT

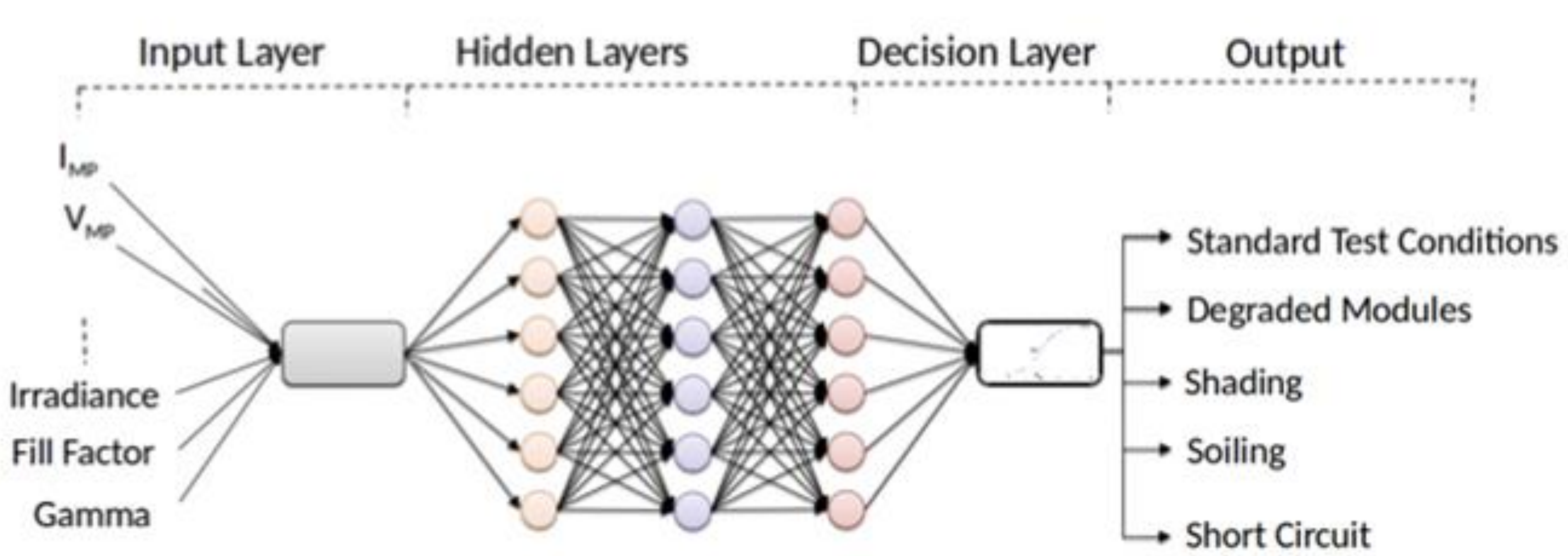
- Neural networks can be used to classify solar faults
- Nonlinear principal component analysis can show redundancies in input features.
- Reducing the dimensions of the input features can simplify the neural network
- The simplified network maintains accuracy.

MOTIVATION

- The current model has difficulty distinguishing between STC and shaded faults.
- Passing the data through a kernel function or encoder NN may be able to separate these classes.
- Not all features may be necessary for the network.
- PCA can inform us to which features are most important.
- Nonlinear PCA methods may be more effective if the input features are nonlinearly dependent.

PROBLEM STATEMENT

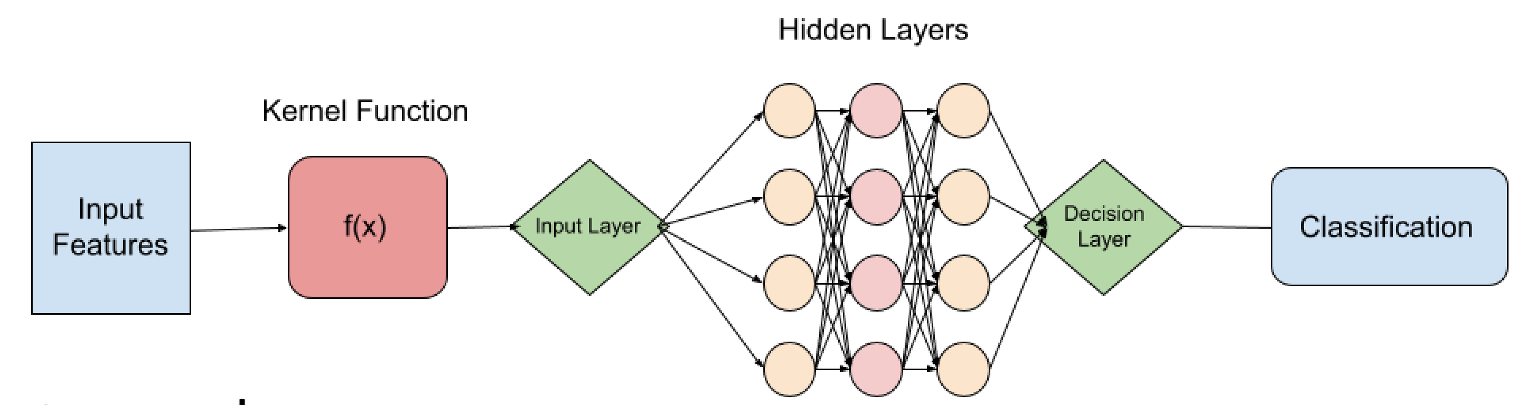
- The importance of PV features in classifying faults is unknown, and the current NN model is unable to distinguish between STC and shaded faults with the current dataset.



EXPERIMENTAL METHODS

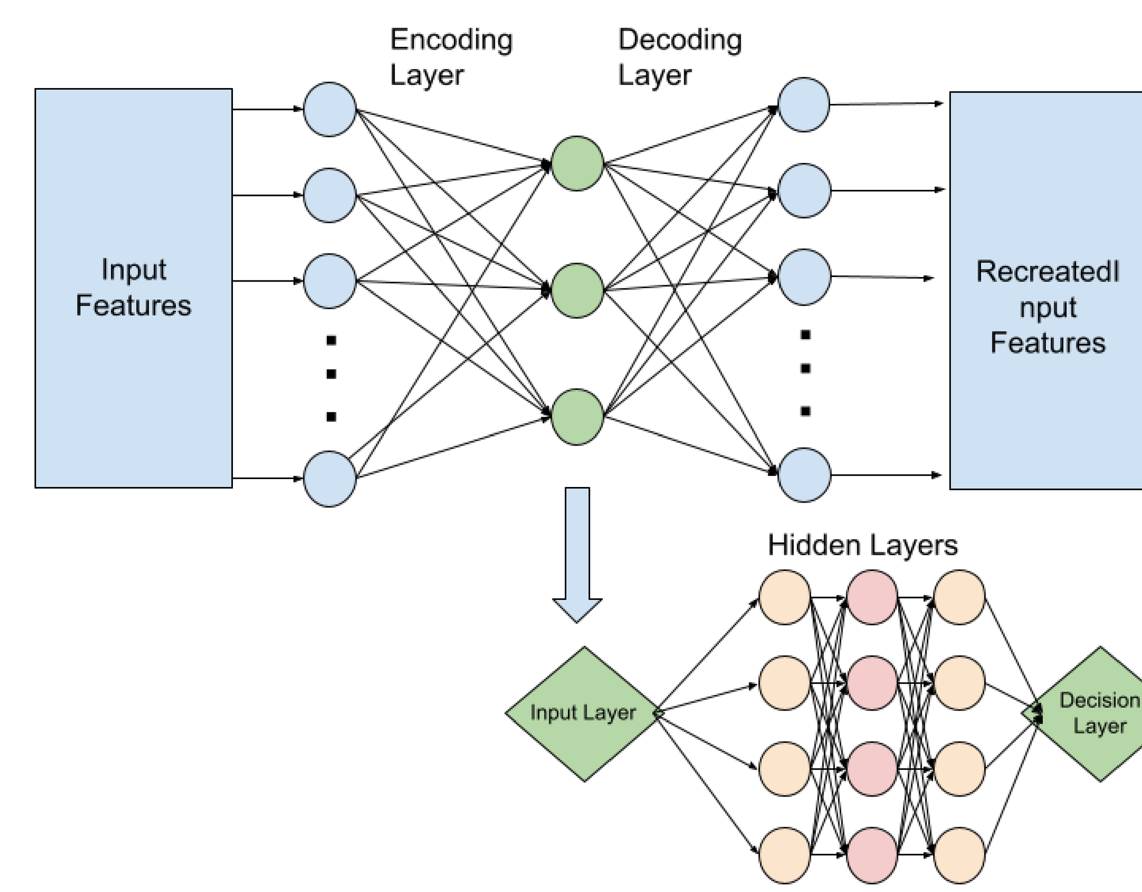
Kernel PCA

- Pass the feature data through multiple kernel functions.
- Select different numbers of input features and pass the modified data into a NN for fault classification.



Autoencoder

- Train a neural network than encodes the data to a specified number of dimension then decodes it.
- Take the output of the encoded layer and pass it into a fault classification NN



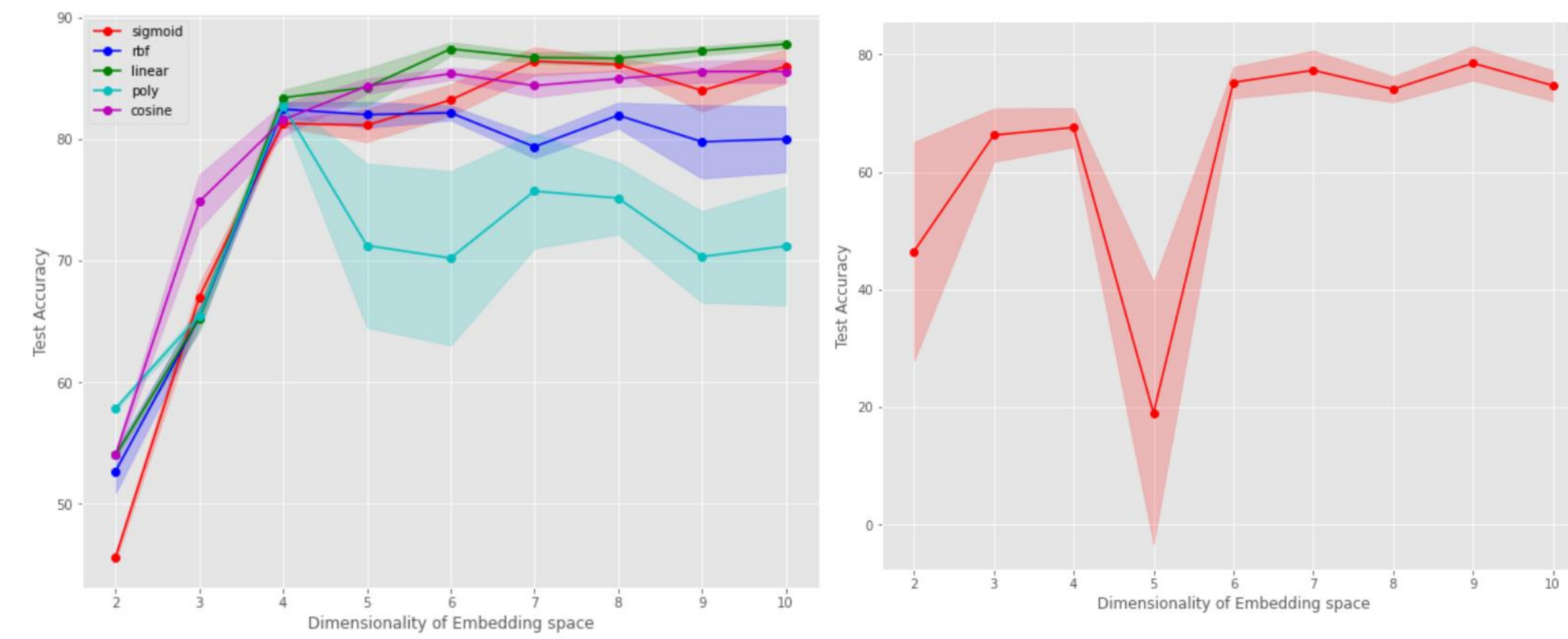
PRELIMINARY RESULTS

Kernel PCA

- Linear Kernel Function is the most accurate
- Classification accuracy levels for 5+ features

Autoencoder

- The autoencoder was less accurate overall with <80% accuracy



REFERENCES

[1] S. Rao, S. Katoch, V. Narayanaswamy, G. Muniraju, C. Tepedelenlioglu,A. Spanias, P. Turaga, R. Ayyanar, and D. Srinivasan, "Machine learningfor solar array monitoring, optimization, and control,"Synthesis Lectureson Power Electronics, vol. 7, no. 1, pp. 1–91, 2020.
[2] S. Wold, K. Esbensen, and P. Geladi, "Principal component analysis,"Chemometrics and intelligent laboratory systems, vol. 2, no. 1-3, pp. 37–52, 1987.
[3] W. W. Hsieh, "Nonlinear principal component analysis by neural net-works,"Tellus A, vol. 53, no. 5, pp. 599–615, 2001.
[4] H. Heiko, "Kernel pca for novelty detection,"Pattern Recognition, vol. 40,no. 3, pp. 863–874, 2007.
[5] R. Shao, H. Wentao, Y. Wang, and Q. Xiankun, "The fault featureextraction and classification of gear using principal component analysisand kernel principal component analysis based on the wavelet packettransform,"Measurement, vol. 54, pp. 118–132, 2014.

ACKNOWLEDGEMENT

- **This project was funded in part by the National Science Foundation, award number 1854273.**

Ira A. Fulton Schools of Engineering, ARIZONA STATE UNIVERSITY

University of Cyprus

Sensor Signal and Information Processing Center
http://sensip.asu.edu

This material is based upon work supported by the National Science Foundation under Grant No. CNS 1659871 REU Site: Sensors, Signal and Information Processing Devices and Algorithms.

NATIONAL SCIENCE FOUNDATION