Feature Analysis for PV Fault Detection Neural Network Using Linear PCA and Random Forest

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Solar facility ASU [1]

Smart Monitoring Device (SMD) [1]
Helps diagnose solar faults

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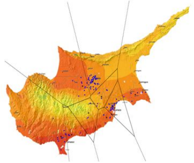

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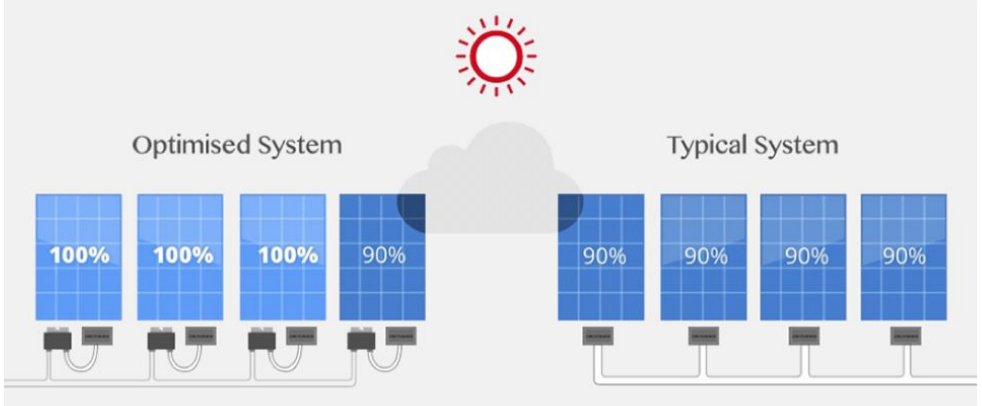
Motivation

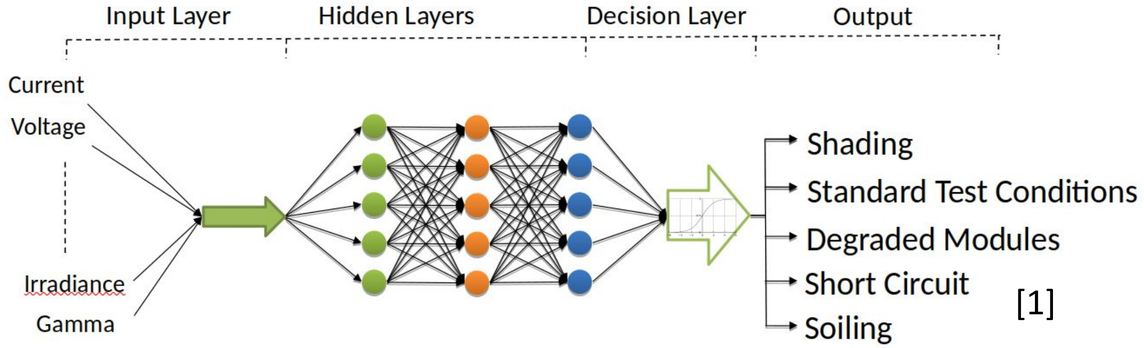
- Solar farms greatly benefit from sensor monitoring systems with the capacity to detect array faults and anomalies.
- Automatic and remote detection and correction of faults elevates the efficiency and robustness of a PV power plant.
- Reduces monitoring and maintenance cost.



Project Aim

- Identify which data features provide the most information to the neural network about classifying solar array faults.
- Reduce redundant or unimportant data

Neural Network architecture



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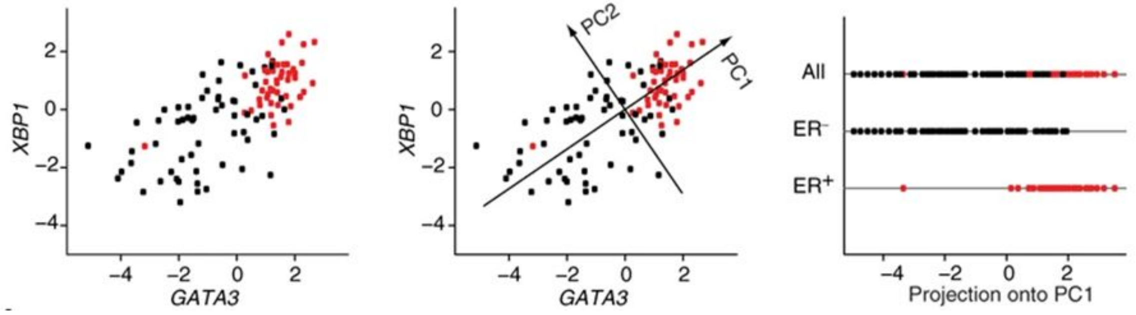
Experimental Methods and ML tools

Linear Principal Component Analysis



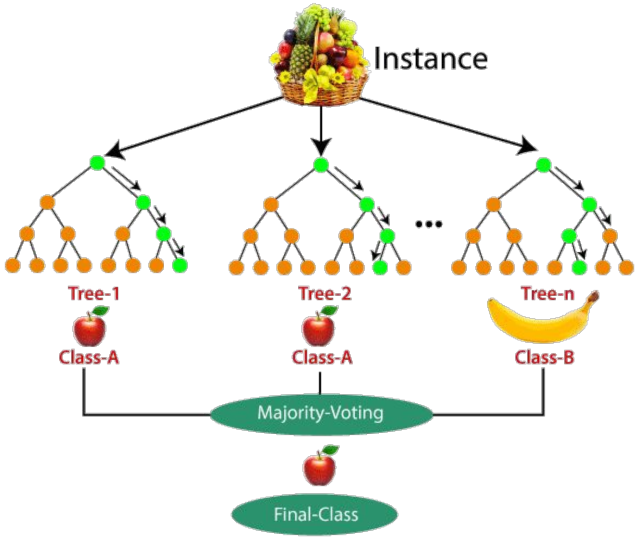
[8]

Implemented via Python

```
In [8]: #Creating neural network
        def NN_model(Dim,pca,X_train, X_test, y_train, y_test):
            x_train = pca.transform(X_train)
            x_test = pca.transform(X_test)
            #transform, just perfroms pca

            OL = 5
            # define the keras model
            model = Sequential()
            model.add(Dense(Dim, input_dim=Dim, activation='relu'))
            model.add(Dense(16, activation='relu'))
            #model.add(Dense(8, activation='relu'))
            model.add(Dense(OL, activation='sigmoid'))

            model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
            model.fit(x_train, y_train, epochs=150, batch_size=128, verbose=1, validation_data=(x_test, y_test)


            # evaluate the keras model
            _, accuracy = model.evaluate(x_test, y_test)
            print('Accuracy: %.2f' % (accuracy*100))

            return accuracy
```

Experimental Methods and ML tools cont...

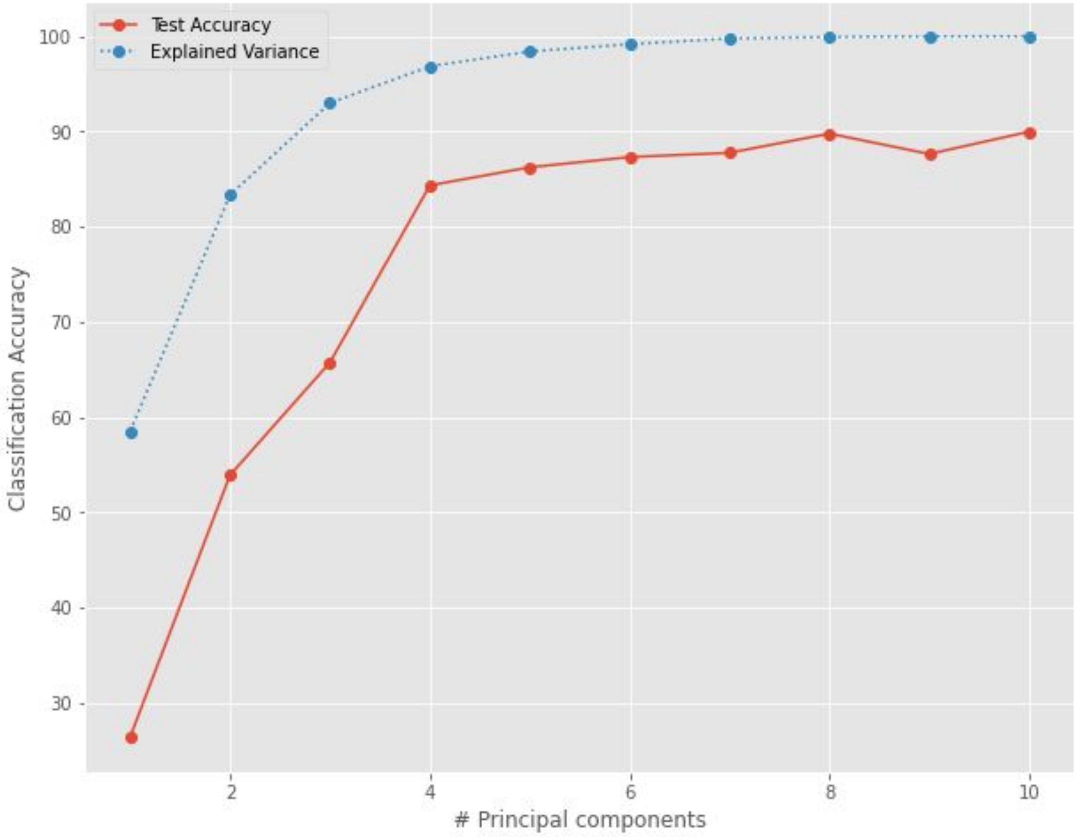
Random Forest Algorithm



Implemented via Python

```
In [6]: feature_names = Data.columns
        feature_names = list(np.array(feature_names[0:9]).astype(str))
        #feature_names = list(np.array(feature_names[0:10]).astype(str))
        print('Feature names : ',feature_names)

        Feature names :  ['DC_Power', 'Vmp', 'Imp', 'Temp', 'Irr', 'Pmp', 'Voc', 'Isc', 'Gamma']

In [7]: forest = RandomForestClassifier(random_state=0)
        forest.fit(X_train, y_train)

Out[7]: RandomForestClassifier(random_state=0)

In [8]: importances = forest.feature_importances_

In [9]: std = np.std([tree.feature_importances_ for tree in forest.estimators_], axis=0)

In [10]: forest_importances = pd.Series(importances, index=feature_names)
```

Linear Principal Component Analysis Results



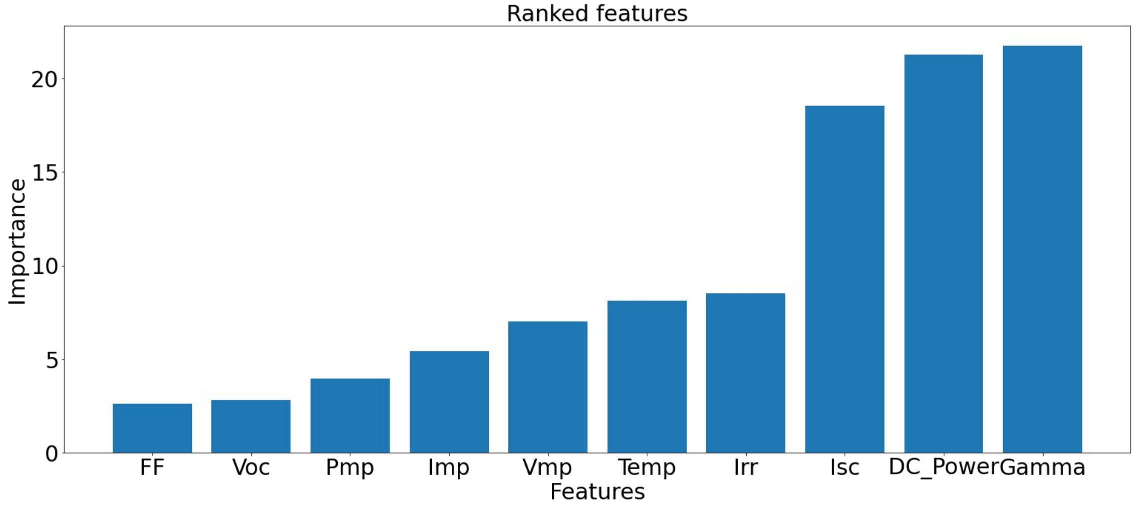
The feature space can be reduced to 4 principal components while retaining 85% accuracy.

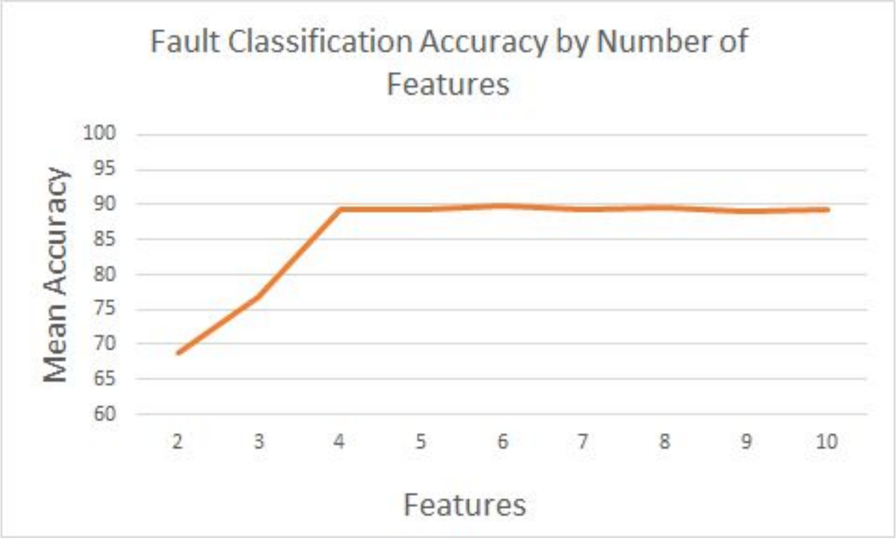
However, the Neural Network does not attain the target accuracy until 8+ principal components.

Data from the National Renewable Energy Laboratory (NREL)

Random Forest Algorithm Results

Using the random forest generated importances, the top 4 features provide the neural network with enough information to classify faults at target accuracy.





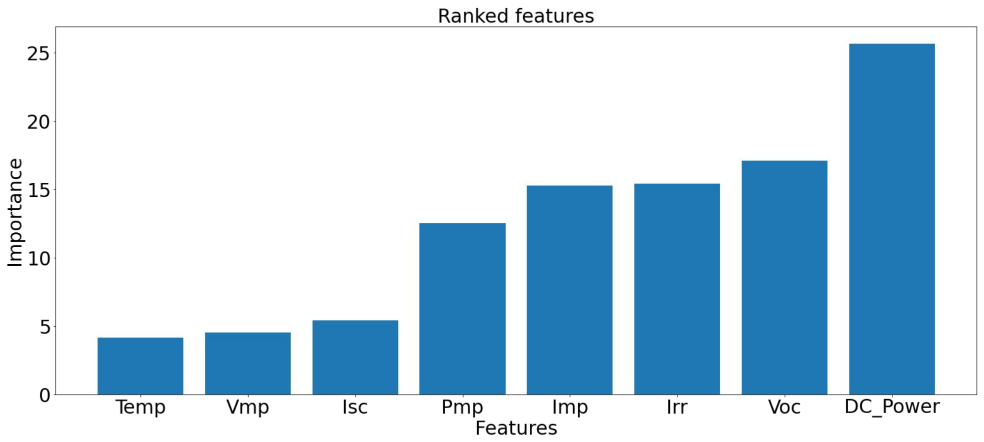
Conclusions

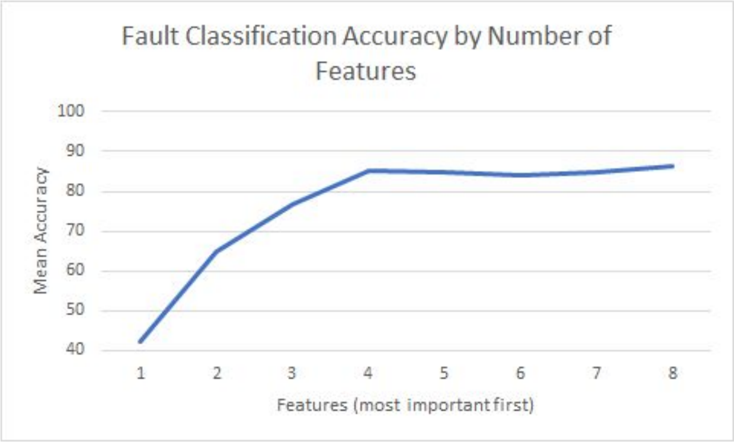
- The feature space can be effectively optimized using both Linear Principal Component Analysis and Random Forest importance rankings.
- The top 4 features in either method accounted for the majority of neural network classification ability.
- Dependent features can play an important role in reducing the feature space

Future Work

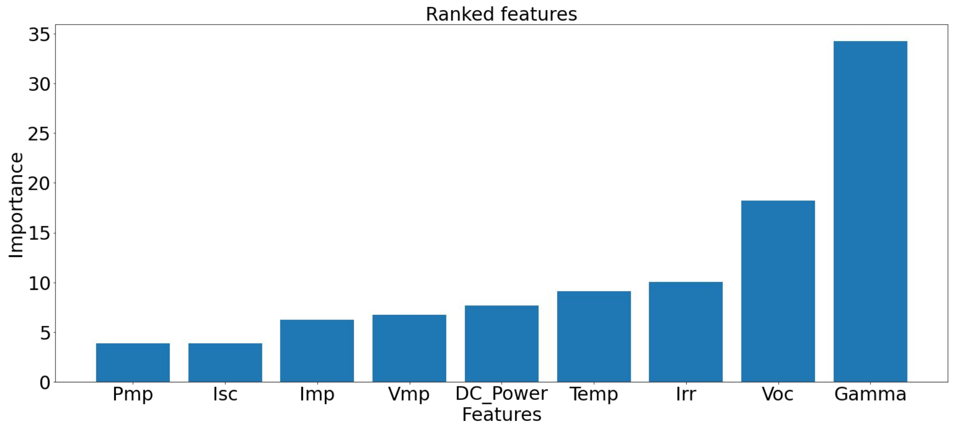
Identifying the role of dependent features (features that are combinations of others)

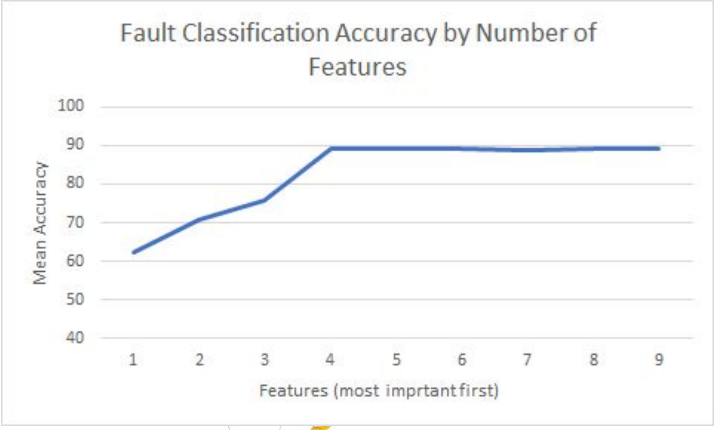
Shown right:
The inclusion of gamma as power divided by irradiance improves overall classification accuracy





Without Gamma





With Gamma

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Challenges and Reflection

- I familiarized myself with several facets of solar panel optimization and solar data.
- I learned data science and machine learning techniques, and implemented them in python.
  - Setting up python environment
  - Reading and writing data from excel
  - PCA, random forest and neural network functionality

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