IBM MACHINE LEARNING - PROJECT C

Fault Classification in Photovoltaic Plants

1 - General Information About the Dataset

This dataset is published by Lazzaretti, A. E. et al. (2020) in a paper named "A Monitoring System for Online Fault Detection and Classification in Photovoltaic Plants" in Sensors journal [1]. The authors collected the data of grid-tie PV panels in a solar plant for 16 consecutive days. The used PV plant has 2 string with 8x C6SU-330P PV Modules each. Both of the strings are attached to a 5kW grid-tie power inverter (NHS Solar 5K-GDM1). The labels in this dataset are used to demonstrate the operation status of the PV, i.e., normal or faulty, and they are as follows,

Label	Meaning	Description
0	Normal Operation	No faults
1	Short-Circuit	Short Circuit between 2 modules of a String
2	Degradation	There is a resistance between 2 modules of a String
3	Open Circuit	One String disconnected from the power inverter
4	Shadowing	Shadow in one or more modules

Furthermore, the independent features descriptions are as follows,

Label	Meaning	Description
Vdc1	String 1 voltage	Direct volt
Vdc2	String 2 voltage	Direct volt
Idc1	String 1 current	Direct current
Idc2	String 2 current	Direct current
irradiance	Sun Irradiance	Watt/square m
pvtemp	PV Temperature	Measured in celsius

Data link on GitHub https://github.com/clayton-h-costa/pv_fault_dataset
The original dataset dimensions are [1,373,798 instances and 7 features], due to limit computational resources, I reduced dataset size by ~58% while also maintaining the ratio approximation. Moreover, the form of data is .mat, I converted it to a csv file in MATLAB using the following code.

MATLAB CODE

load('dataset_elec.mat')

load('dataset_amb.mat')

% most columns need to be transposed.

Idc1 = idc1';

Idc2 = idc2';

irradiance = irr';

pvtemp = pvt';

Vdc1 = vdc1';

Vdc2 = vdc2';

myT = table(Idc1,Idc2,Vdc1,Vdc2,irradiance,pvtemp,f_nv); % Creating the table

head(myT)

writetable(myT,'PVdata.csv') % export to a csv file.

2 - Analysis Objectives

A - to find the impact of voltage, current, irradiance, and temperature on PV panels.
B - To reduce the imbalance between classes effect.
C - To use GridSearchCV to find the best parameters.
D - To benchmark Logisitc Regression vs Decision Tree vs RandomForest.

In [1]:
```
# Dataframe and plotting libraries
import numpy as np # For linear algebra
import pandas as pd # For data frame manipulation
import seaborn as sns # For visualization I
import matplotlib.pyplot as plt # For visualization II


# Machine Learing libraries
from sklearn.linear_model import LogisticRegression # Model 1
from sklearn.tree import DecisionTreeClassifier # Model 2
from sklearn.ensemble import RandomForestClassifier # Model 3


from sklearn.model_selection import StratifiedShuffleSplit # To stratify spl
from sklearn.model_selection import StratifiedKFold # To stratify kfolds
from sklearn.model_selection import GridSearchCV # To find best parameters
from sklearn.metrics import accuracy_score, precision_recall_fscore_support
from sklearn.metrics import classification_report # To evaluate models
from sklearn.metrics import confusion_matrix # To plot models outcome


from sklearn.preprocessing import MinMaxScaler # To scale data
from imblearn.under_sampling import RandomUnderSampler # To undersample data
from imblearn.over_sampling import RandomOverSampler, SMOTE # To oversample


# Utility library
import pickle # Save the ML object model.
import os # To access directory
import warnings  # To mute warnings
```

```
warnings.filterwarnings("ignore") # Mute warning
os.chdir('/Users/salahkaf/Desktop/data') # Changing working directory


%matplotlib inline
```

In [2]:

```
# Defining auxiliary function 1
rs = 123 # Setting random state to '123' in all models and sampling.

# Defining auxiliary function 2
# evaluation metrics stored in a dictionary
def evaluate_metrics(yt, yp):
    results_pos = {}
    results_pos['accuracy'] = accuracy_score(yt, yp)

    precision, recall, f_beta, _ = precision_recall_fscore_support(yt, yp)
    W_precision, W_recall, W_fbeta, _ = precision_recall_fscore_support(yt,

    results_pos['precision'] = precision
    results_pos['Weighted precision'] = W_precision
    results_pos['recall'] = recall
    results_pos['Weighted recall'] = W_recall
    results_pos['f1score'] = f_beta
    results_pos['Weighted f1score'] = W_fbeta
    return results_pos
```

In [3]:

```
df = pd.read_csv('PVdata.csv', sep  = ',')# Reading the df
```

Basic understanding about the dataset

In [4]:

```
print('The dataset first three rows are')
display(df.head(3))
print('')
print('The dataset last three rows are')
display(df.tail(3))
```

The dataset first three rows are

	Idc1	Idc2	Vdc1	Vdc2	irradiance	pvtemp	f_nv
0	0.0646	0.0067	0.7110	0.5583	1.5118	2.3883	0
1	0.0628	0.0067	0.6991	0.5465	1.5534	2.3920	0
2	0.0606	0.0076	0.7035	0.5553	1.4355	2.3920	0

The dataset last three rows are

	Idc1	Idc2	Vdc1	Vdc2	irradiance	pvtemp	f_nv
583061	0.1067	0.0359	0.5447	0.6187	0.9478	10.4333	0
583062	0.1118	0.0360	0.5621	0.6327	0.9769	10.4333	0
583063	0.1121	0.0370	0.5352	0.6221	1.1632	10.4313	0

In [5]:

```
print(f'The data frame encompasses {df.shape[0]} instances and {df.shape[1]}
print('The features data types are as follows,')
print(df.dtypes.value_counts())
```

```
The data frame encompasses 583064 instances and 7 features

The features data types are as follows,
float64    6
int64      1
dtype: int64
```

In [6]:
```
print('Checking for missing values per column:')
print(df.isna().sum())
```

```
Checking for missing values per column:
Idc1          0
Idc2          0
Vdc1          0
Vdc2          0
irradiance    0
pvtemp        0
f_nv          0
dtype: int64
```

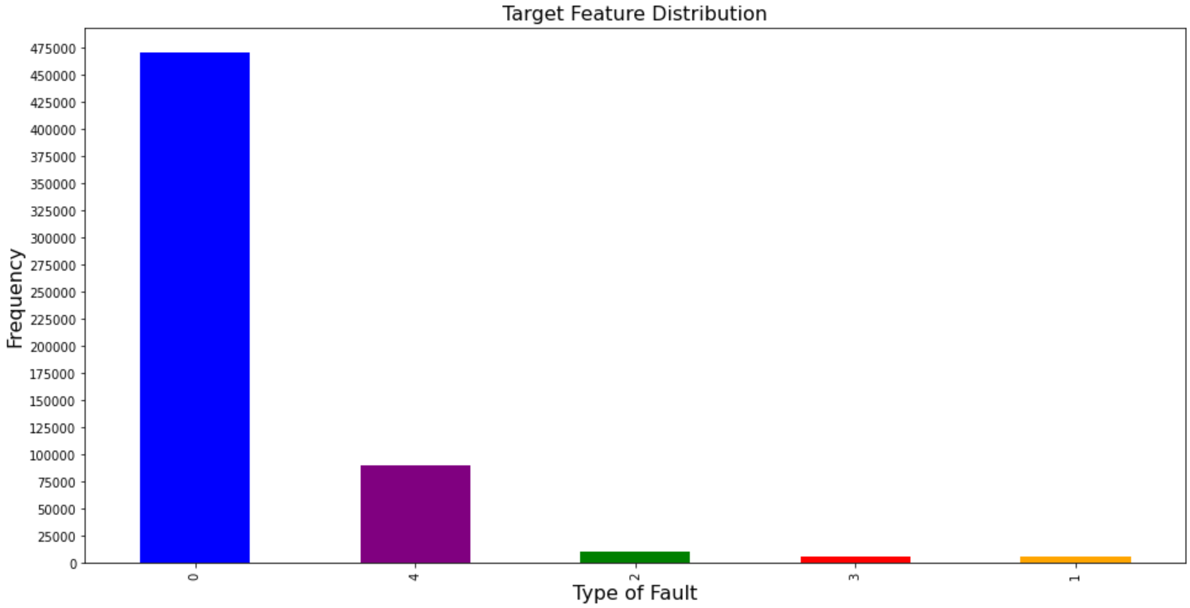
In [7]:
```
print('The target feature is class, i.e., fault type, distributed in the dat
print(df['f_nv'].value_counts())
print('')
print('the ratios of classes are as follows')
print(df['f_nv'].value_counts(normalize = True))
```

```
The target feature is class, i.e., fault type, distributed in the dataset as
follows,
0    470714
4     89956
2     10371
3      6024
1      5999
Name: f_nv, dtype: int64

the ratios of classes are as follows
0    0.807311
4    0.154282
2    0.017787
3    0.010332
1    0.010289
Name: f_nv, dtype: float64
```

In [8]:
```
# Plotting the ratio between classes
from matplotlib.pyplot import figure

fig, ax = plt.subplots(figsize=(16, 8))
df['f_nv'].value_counts().plot.bar(color= ['blue','purple','green','red','or
ax.set_ylabel('Frequency',fontsize=16)
ax.set_xlabel('Type of Fault',fontsize=16)
ax.set_title('Target Feature Distribution',fontsize=16)
ax.locator_params('y', nbins=20)
plt.show()
```



We observe that classes are extremely skewed, because 80% of them are labled as '0', i.e., normal operation. To solve this matter, we will fit a logistic regression model and make predictions using the original dataset, and compare the results with a downsampled dataset, a rewighted datset, and resampled dataset. Then, the dataset that achieves the highest average score will be used to fit and evaluate other classification algorithms.

Moreover, resampling techniques will be applied only after doing validation-split to ensure that we mimic real world scenarios.

In [9]:
```
# Identifying the feature columns
feature_cols = df.drop('f_nv',axis = 1).columns.tolist()
feature_cols
```

Out[9]:
```
['Idc1', 'Idc2', 'Vdc1', 'Vdc2', 'irradiance', 'pvtemp']
```

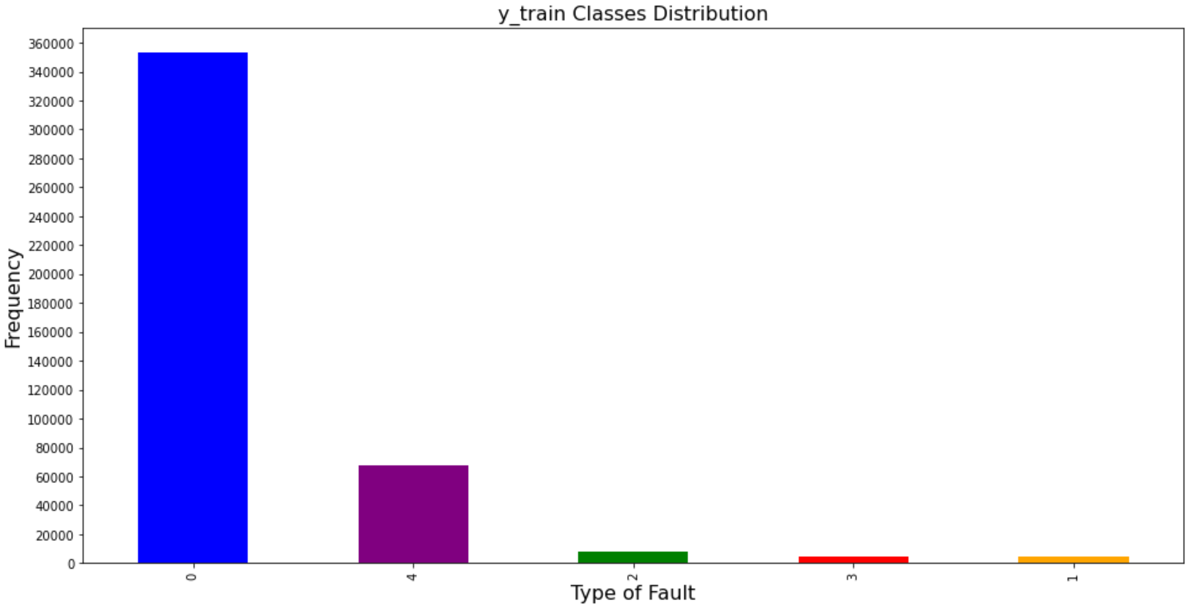
In [10]:
```
# Get the split indexes
strat_shuf_split = StratifiedShuffleSplit(n_splits=1,
                                          test_size=0.25, # 25% to validate
                                          random_state=rs)

# We use 'next' to get the arrays from the generator object.
train_idx, test_idx = next(strat_shuf_split.split(df[feature_cols], df['f_nv
# next(strat_shuf_split.split(dataframe[feature_cols], dataframe['class']))
```

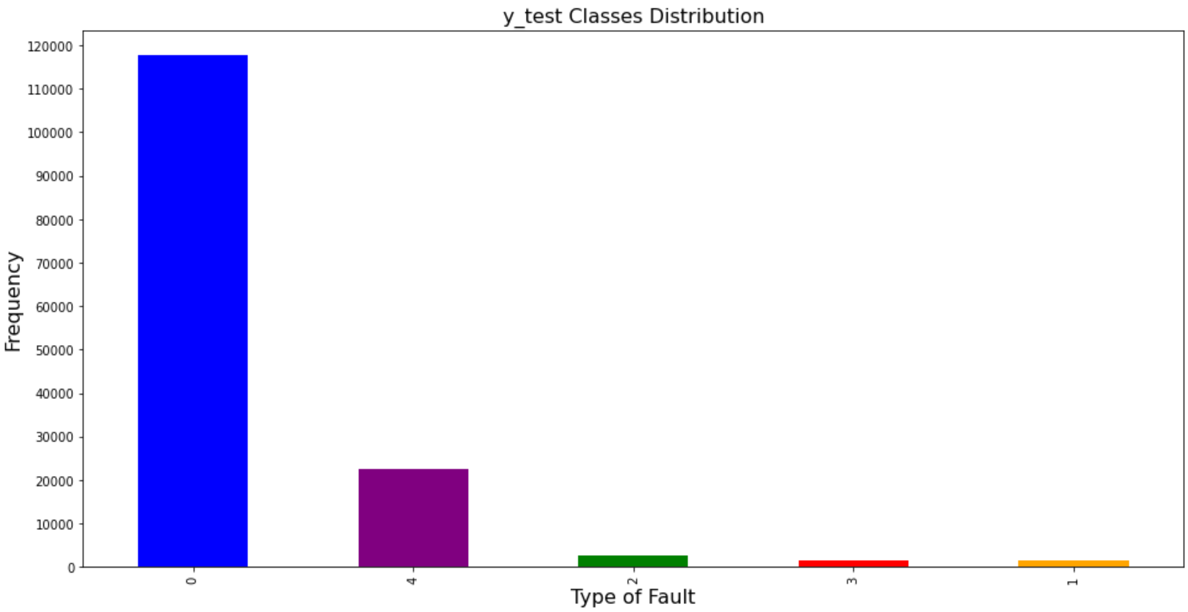
In [11]:
```
# Create the train and test sets
X_train = df.loc[train_idx, feature_cols] # loc[index,column]
y_train = df.loc[train_idx, 'f_nv']

X_test  = df.loc[test_idx, feature_cols]
y_test  = df.loc[test_idx, 'f_nv']
```

In [12]:
```
# Plotting y_train distribution
fig, ax = plt.subplots(figsize=(16, 8))
y_train.value_counts().plot.bar(color= ['blue','purple','green','red','orang
ax.set_xlabel('Type of Fault',fontsize=16)
ax.set_ylabel('Frequency',fontsize=16)
ax.set_title('y_train Classes Distribution',fontsize=16)
ax.locator_params('y', nbins=20)
plt.show()
```



In [13]:
```
# Plotting y_test distribution
fig, ax = plt.subplots(figsize=(16, 8))
y_test.value_counts().plot.bar(color= ['blue','purple','green','red','orange
ax.set_xlabel('Type of Fault',fontsize=16)
ax.set_ylabel('Frequency',fontsize=16)
ax.set_title('y_test Classes Distribution',fontsize=16)
ax.locator_params('y', nbins=20)
plt.show()
```



A - First Approach (Reweighting classes)

In [14]:
```
y_train.value_counts()
```

Out[14]:
```
0    353036
4     67467
2      7778
3      4518
1      4499
Name: f_nv, dtype: int64
```

In [15]:
```
# Initially, let's scale data using min-max scaler.
scaler = MinMaxScaler()
```

```
X_train_s = scaler.fit_transform(X_train) # Fit and transform.
X_test_s = scaler.transform(X_test) # transform only.
```

In [16]:
```
class_weight = {}
# Weighting is approximated based on number of classes.
class_weight[0] = 0.05
class_weight[1] = 0.30
class_weight[2] = 0.20
class_weight[3] = 0.30
class_weight[4] = 0.15
```

In [17]:
```
# Define a logistic regression with weight
model = LogisticRegression(solver='saga', random_state=rs, class_weight=clas
model.fit(X_train_s, y_train)
preds =  model.predict(X_test_s)
```

In [18]:
```
# Results
reweighted = evaluate_metrics(y_test,preds)
reweighted
```

Out[18]:
```
{'accuracy': 0.9039282137123883,
 'precision': array([0.9611271 , 0.98031496, 0.49903148, 0.99209486, 0.71112
904]),
 'Weighted precision': 0.9148543006241275,
 'recall': array([0.91942419, 0.996     , 0.79483224, 1.        , 0.8228467
3]),
 'Weighted recall': 0.9039282137123883,
 'f1score': array([0.93981325, 0.98809524, 0.61311914, 0.99603175, 0.7629197
5]),
 'Weighted f1score': 0.9077880307113514}
```

In [19]:
```
# Storing evaluation metrics (average values)
reweighted_results = list()
keys = ['accuracy','Weighted precision','Weighted recall','Weighted f1score'
for key in keys:
       reweighted_results.append(reweighted.get(key))
reweighted_results
```

Out[19]:
```
[0.9039282137123883,
 0.9148543006241275,
 0.9039282137123883,
 0.9077880307113514]
```

In [20]:
```
# storing evaluation metrics (per class)
reweighted_rpf = []
elements = ['precision','recall','f1score']
for element in elements:
       reweighted_rpf.append(reweighted.get(element))
reweighted_rpf
```

Out[20]:
```
[array([0.9611271 , 0.98031496, 0.49903148, 0.99209486, 0.71112904]),
 array([0.91942419, 0.996     , 0.79483224, 1.        , 0.82284673]),
 array([0.93981325, 0.98809524, 0.61311914, 0.99603175, 0.76291975])]
```

B - Second Approach [Undersampling]

In [21]:
```
under_sampler = RandomUnderSampler(random_state=rs) #initiating undersamplin
X_under, y_under = under_sampler.fit_resample(X_train_s, y_train)
```

In [22]:
```
print('y_train after undersampling')
y_under.value_counts()
```

```
y_train after undersampling
```

Out[22]:
```
0    4499
1    4499
2    4499
3    4499
4    4499
Name: f_nv, dtype: int64
```

In [23]:
```
model = LogisticRegression(solver='saga', random_state=rs)
model.fit(X_under, y_under)
preds = model.predict(X_test_s)
```

In [24]:
```
undersampling = evaluate_metrics(y_test,preds)
undersampling
```

Out[24]:
```
{'accuracy': 0.7925304940795521,
 'precision': array([0.98144409, 0.98548813, 0.17477876, 0.99209486, 0.55353
008]),
 'Weighted precision': 0.9012269253809336,
 'recall': array([0.76003161, 0.996     , 0.97493251, 1.        , 0.9140913
3]),
 'Weighted recall': 0.7925304940795521,
 'f1score': array([0.85666258, 0.99071618, 0.29641789, 0.99603175, 0.6895198
5]),
 'Weighted f1score': 0.8237288574398645}
```

In [25]:
```
# Storing evaluation metrics (average values)
undersampling_results = list()
for key in keys:
        undersampling_results.append(undersampling.get(key))
undersampling_results
```

Out[25]:
```
[0.7925304940795521,
 0.9012269253809336,
 0.7925304940795521,
 0.8237288574398645]
```

In [26]:
```
# storing evaluation metrics (per class)
undersampling_rpf = []
for element in elements:
        undersampling_rpf.append(undersampling.get(element))
undersampling_rpf
```

Out[26]:
```
[array([0.98144409, 0.98548813, 0.17477876, 0.99209486, 0.55353008]),
 array([0.76003161, 0.996     , 0.97493251, 1.        , 0.91409133]),
 array([0.85666258, 0.99071618, 0.29641789, 0.99603175, 0.68951985])]
```

C - Third Apporach [Resampling]

In [27]:
```
smote_sampler = SMOTE(random_state = rs) #Initiating SMOTE sampler
X_smo, y_smo = smote_sampler.fit_resample(X_train_s, y_train)
```

In [28]:
```
y_smo.value_counts()
```

Out[28]:
```
0    353036
4    353036
1    353036
3    353036
2    353036
Name: f_nv, dtype: int64
```

In [29]:
```
model = LogisticRegression(solver='saga', random_state=rs)
```

In [30]:
```
model.fit(X_smo, y_smo)
```

```
preds = model.predict(X_test_s)
```

In [31]:
```
resampling = evaluate_metrics(y_test, preds)
resampling
```

Out[31]:
```
{'accuracy': 0.8886434422293265,
 'precision': array([0.9832507 , 0.95028681, 0.46295961, 0.98560209, 0.64429
823]),
 'Weighted precision': 0.921386329463096,
 'recall': array([0.87798059, 0.994     , 0.98573081, 1.        , 0.9187602
8]),
 'Weighted recall': 0.8886434422293265,
 'f1score': array([0.92763864, 0.971652  , 0.63002218, 0.99274885, 0.7574324
6]),
 'Weighted f1score': 0.89721034685069}
```

In [32]:
```
# Storing evaluation metrics (average values)
resampling_results = list()
for key in keys:
       resampling_results.append(resampling.get(key))
resampling_results
```

Out[32]:
```
[0.8886434422293265, 0.921386329463096, 0.8886434422293265, 0.8972103468506
9]
```

In [33]:
```
# storing evaluation metrics (per class)
resampling_rpf = []
for element in elements:
       resampling_rpf.append(resampling.get(element))
resampling_rpf
```

Out[33]:
```
[array([0.9832507 , 0.95028681, 0.46295961, 0.98560209, 0.64429823]),
 array([0.87798059, 0.994     , 0.98573081, 1.        , 0.91876028]),
 array([0.92763864, 0.971652  , 0.63002218, 0.99274885, 0.75743246])]
```

In [34]:
```
final_results= {
    'Metric': ['Accuracy',' Weighted Recall','Weighted Precision','Weighted
    'Rewieghted' :reweighted_results,
    'Undersampled':undersampling_results,
    'Resampled':resampling_results}
final_results = pd.DataFrame(final_results).set_index('Metric')
display(final_results)
```

Metric	Rewieghted	Undersampled	Resampled
Accuracy	0.903928	0.792530	0.888643
Weighted Recall	0.914854	0.901227	0.921386
Weighted Precision	0.903928	0.792530	0.888643
Weighted F1score	0.907788	0.823729	0.897210

In [35]:
```
final_results_per_class = {
    'classes': [0,1,2,3,4],
    'Rewieghted recall' :reweighted_rpf[0],
    'Rewieghted Precision' :reweighted_rpf[1],
    'Rewieghted F1score' :reweighted_rpf[2],
    'Undersampled recall':undersampling_rpf[0],
    'Undersampled precision':undersampling_rpf[1],
    'Undersampled F1 score':undersampling_rpf[2],
    'Resampled recall':resampling_rpf[0],
    'Resampled precision':resampling_rpf[1],
```

```
    'Resampled F1 score':resampling_rpf[2]}
final_results_per_class = pd.DataFrame(final_results_per_class).set_index('c
final_results_per_class.T
```

Out[35]:

classes	0	1	2	3	4
Rewieghted recall	0.961127	0.980315	0.499031	0.992095	0.711129
Rewieghted Precision	0.919424	0.996000	0.794832	1.000000	0.822847
Rewieghted F1score	0.939813	0.988095	0.613119	0.996032	0.762920
Undersampled recall	0.981444	0.985488	0.174779	0.992095	0.553530
Undersampled precision	0.760032	0.996000	0.974933	1.000000	0.914091
Undersampled F1 score	0.856663	0.990716	0.296418	0.996032	0.689520
Resampled recall	0.983251	0.950287	0.462960	0.985602	0.644298
Resampled precision	0.877981	0.994000	0.985731	1.000000	0.918760
Resampled F1 score	0.927639	0.971652	0.630022	0.992749	0.757432

Based on the above findings, reweighting is the best technique in terms of overall performance. Ergo, the classes will be reweighted accordingly in all the machine learning models.

Machine Learning Models

Steps:

1 - Initiating 4 stratified folds.

2 - Run GridSearch on LR, DT, and RF.

3 - Benchmark the models.

4 - Select the most appropriate model.

In [36]:
```
kf = StratifiedKFold(shuffle=True, random_state=rs , n_splits= 4 ) # 4 split
```

In [37]:
```
# Identifying the param_grid to loop through it using GridSearchCV
param_grid = {'C':[0.1,1,10],
              'penalty':['l1', 'l2']}
model = LogisticRegression(random_state = rs, class_weight=class_weight, sol
```

In [38]:
```
search_lr = GridSearchCV(estimator=model,
                      param_grid=param_grid,
                      scoring='accuracy',
                      cv=kf,
                      n_jobs= -1)
search_lr.fit(X_train_s, y_train)
```

```
/opt/anaconda3/lib/python3.9/site-packages/sklearn/linear_model/_sag.py:352:
ConvergenceWarning: The max_iter was reached which means the coef_ did not c
onverge
  warnings.warn(
/opt/anaconda3/lib/python3.9/site-packages/sklearn/linear_model/_sag.py:352:
ConvergenceWarning: The max_iter was reached which means the coef_ did not c
onverge
  warnings.warn(
/opt/anaconda3/lib/python3.9/site-packages/sklearn/linear_model/_sag.py:352:
ConvergenceWarning: The max_iter was reached which means the coef_ did not c
onverge
  warnings.warn(
/opt/anaconda3/lib/python3.9/site-packages/sklearn/linear_model/_sag.py:352:
ConvergenceWarning: The max_iter was reached which means the coef_ did not c
onverge
  warnings.warn(
/opt/anaconda3/lib/python3.9/site-packages/sklearn/linear_model/_sag.py:352:
ConvergenceWarning: The max_iter was reached which means the coef_ did not c
onverge
  warnings.warn(
/opt/anaconda3/lib/python3.9/site-packages/sklearn/linear_model/_sag.py:352:
ConvergenceWarning: The max_iter was reached which means the coef_ did not c
onverge
  warnings.warn(
/opt/anaconda3/lib/python3.9/site-packages/sklearn/linear_model/_sag.py:352:
ConvergenceWarning: The max_iter was reached which means the coef_ did not c
onverge
  warnings.warn(
/opt/anaconda3/lib/python3.9/site-packages/sklearn/linear_model/_sag.py:352:
ConvergenceWarning: The max_iter was reached which means the coef_ did not c
onverge
  warnings.warn(
```

Out[38]:
```
GridSearchCV(cv=StratifiedKFold(n_splits=4, random_state=123, shuffle=True),
             estimator=LogisticRegression(class_weight={0: 0.05, 1: 0.3, 2:
0.2,
                                                         3: 0.3, 4: 0.15},
                                          random_state=123, solver='saga'),
             n_jobs=-1, param_grid={'C': [0.1, 1, 10], 'penalty': ['l1', 'l
2']},
             scoring='accuracy')
```

In [39]:
```
search_lr.best_score_
```

Out[39]:
```
0.9286962244276853
```

In [40]:
```
search_lr.best_params_
```

Out[40]:
```
{'C': 10, 'penalty': 'l1'}
```

In [41]:
```
lr_model = LogisticRegression(random_state = rs, C = 10, penalty = 'l1', sol
```

In [42]:
```
lr_model.fit(X_train_s, y_train)
```

Out[42]:
```
LogisticRegression(C=10, penalty='l1', random_state=123, solver='saga')
```

In [43]:
```
preds = lr_model.predict(X_test_s)
```

In [44]:
```
logistic = evaluate_metrics(y_test, preds)
logistic # results dict
```

Out[44]:
```
{'accuracy': 0.9246189097594775,
 'precision': array([0.93230996, 0.98546896, 0.9750904 , 0.99274885, 0.84833
213]),
 'Weighted precision': 0.9212862066234055,
 'recall': array([0.97905301, 0.99466667, 0.93598149, 1.        , 0.6287518
3]),
 'Weighted recall': 0.9246189097594775,
 'f1score': array([0.95510992, 0.99004645, 0.95513577, 0.99636123, 0.7222208
]),
 'Weighted f1score': 0.9199656032184426}
```

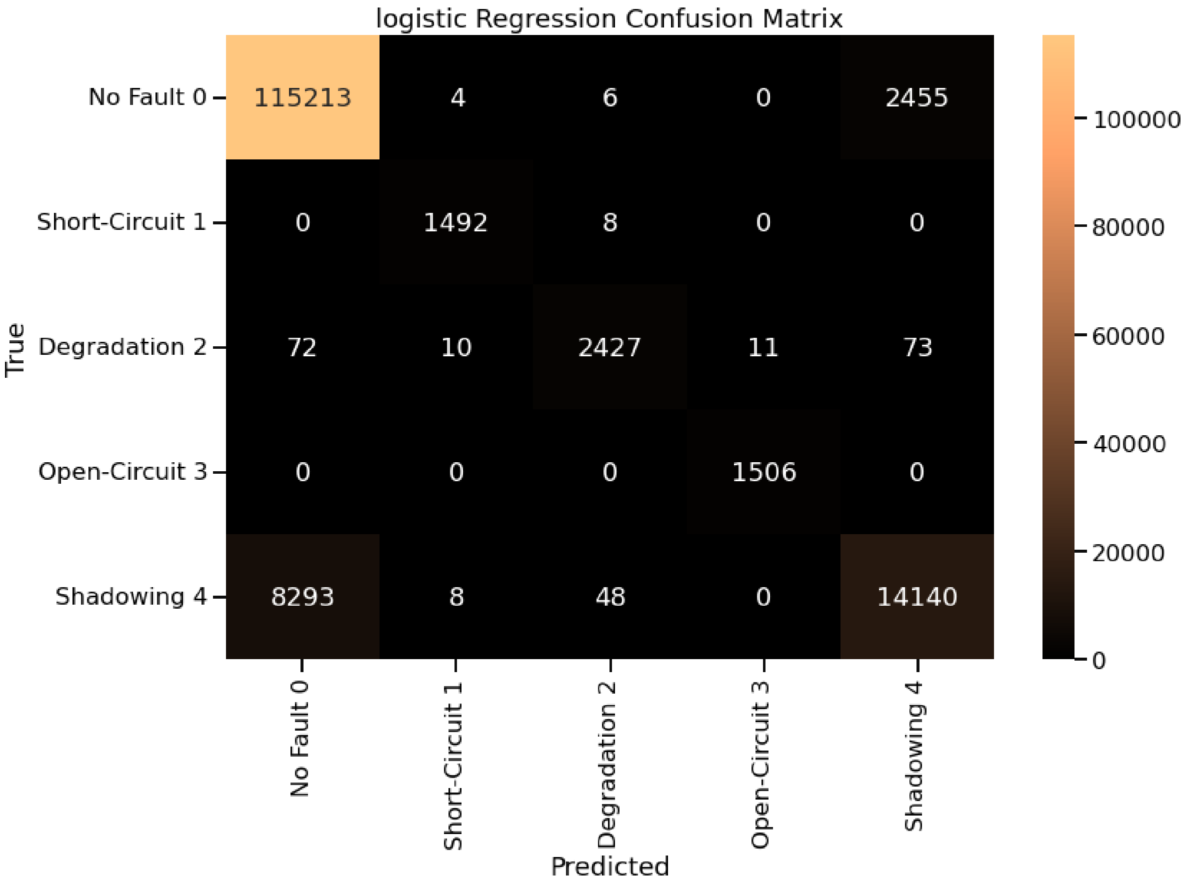
In [45]:
```
# Results in more understandable manner
print(classification_report(y_test, preds))

sns.set_context('talk')
cm = confusion_matrix(y_test, preds)
plt.figure(figsize = (12,8))
ax = sns.heatmap(cm, annot=True, fmt='d', cmap='copper',
                xticklabels=['No Fault 0', 'Short-Circuit 1', 'Degradation 2
                 yticklabels=['No Fault 0', 'Short-Circuit 1', 'Degradation
ax.set(title="logistic Regression Confusion Matrix");
ax.set_xlabel('Predicted');
ax.set_ylabel('True');
```

```
              precision    recall  f1-score   support

           0       0.93      0.98      0.96    117678
           1       0.99      0.99      0.99      1500
           2       0.98      0.94      0.96      2593
           3       0.99      1.00      1.00      1506
           4       0.85      0.63      0.72     22489

    accuracy                           0.92    145766
   macro avg       0.95      0.91      0.92    145766
weighted avg       0.92      0.92      0.92    145766
```



In [46]:
```
#Storing evaluation metrics (average values)
lr_results = list()
for key in keys:
        lr_results.append(logistic.get(key))
lr_results
```

Out[46]:
```
[0.9246189097594775,
 0.9212862066234055,
 0.9246189097594775,
 0.9199656032184426]
```

In [47]:
```
# storing evaluation metrics (per class)
lr_rpf = []
for element in elements:
        lr_rpf.append(logistic.get(element))
lr_rpf
```

Out[47]:
```
[array([0.93230996, 0.98546896, 0.9750904 , 0.99274885, 0.84833213]),
 array([0.97905301, 0.99466667, 0.93598149, 1.        , 0.62875183]),
 array([0.95510992, 0.99004645, 0.95513577, 0.99636123, 0.7222208 ])]
```

In [48]:
```
# this will help us to resote the object even if the kernal is shutdown
pickle.dump(search_lr, open('search_lr.p','wb')) # write it as bytes
pickle.dump(lr_model, open('lr_model.p','wb')) # write it as bytes
```

In [49]:
```
# Identifying the param_grid to loop through it using GridSearchCV

param_grid = {'criterion':['gini','entropy'],
              'max_depth':[1,3,5,7],
              'max_features' :[2,4,6]}
model = DecisionTreeClassifier(random_state = rs, class_weight = class_weigh
```

In [50]:
```
search_dt = GridSearchCV(estimator=model,
                      param_grid=param_grid,
                      scoring='accuracy',
                      cv=kf,
                      n_jobs = -1) # Initiate search object
search_dt.fit(X_train_s, y_train)
```

Out[50]:
```
GridSearchCV(cv=StratifiedKFold(n_splits=4, random_state=123, shuffle=True),
             estimator=DecisionTreeClassifier(class_weight={0: 0.05, 1: 0.3,
                                                              2: 0.2, 3: 0.3,
                                                              4: 0.15},
                                              random_state=123),
             n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [1, 3, 5, 7], 'max_features': [2, 4,
6]},
             scoring='accuracy')
```

In [51]:
```
search_dt.best_score_
```

Out[51]:
```
0.9645847835451163
```

In [52]:
```
search_dt.best_params_
```

Out[52]:
```
{'criterion': 'gini', 'max_depth': 7, 'max_features': 4}
```

In [53]:
```
dt_model = DecisionTreeClassifier(random_state = rs, criterion = 'gini',
                            max_features = 4, max_depth =7, class_weig
dt_model.fit(X_train_s, y_train)
preds = dt_model.predict(X_test_s)
```

In [54]:
```
tree = evaluate_metrics(y_test, preds)
tree
```

Out[54]:
```
{'accuracy': 0.9682642042726013,
 'precision': array([0.99374204, 0.96881092, 0.91029307, 0.99602912, 0.85779
672]),
 'Weighted precision': 0.9710508060959091,
 'recall': array([0.96753004, 0.994     , 0.98225993, 0.99933599, 0.9666948
3]),
 'Weighted recall': 0.9682642042726013,
 'f1score': array([0.98046088, 0.98124383, 0.94490818, 0.99767981, 0.9089958
8]),
 'Weighted f1score': 0.9689886675918266}
```

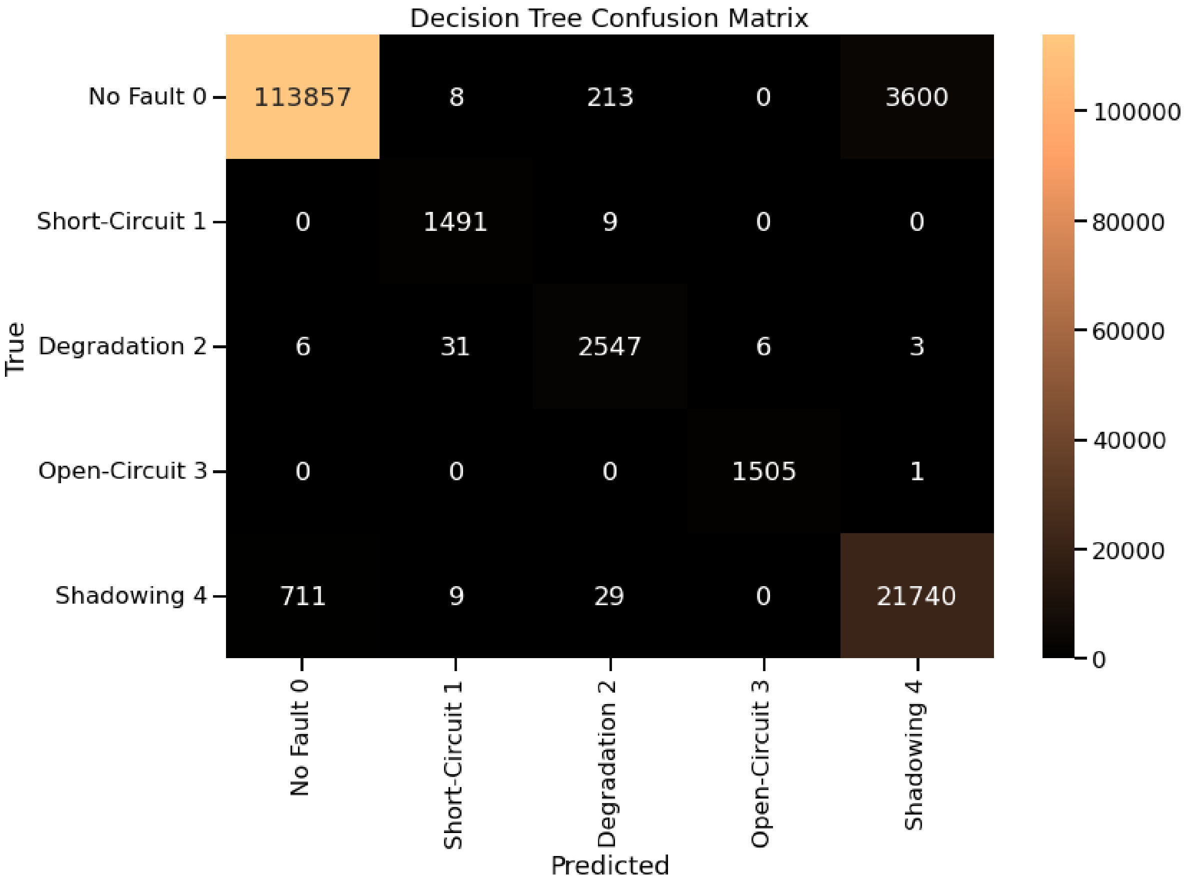
In [55]:
```
print(classification_report(y_test, preds))

sns.set_context('talk')
cm = confusion_matrix(y_test, preds)
plt.figure(figsize = (12,8))
ax = sns.heatmap(cm, annot=True, fmt='d', cmap='copper',
                xticklabels=['No Fault 0', 'Short-Circuit 1', 'Degradation 2
                 yticklabels=['No Fault 0', 'Short-Circuit 1', 'Degradation
ax.set(title="Decision Tree Confusion Matrix");
ax.set_xlabel('Predicted');
ax.set_ylabel('True');
```

```
              precision    recall  f1-score   support

           0       0.99      0.97      0.98    117678
           1       0.97      0.99      0.98      1500
           2       0.91      0.98      0.94      2593
           3       1.00      1.00      1.00      1506
           4       0.86      0.97      0.91     22489

    accuracy                           0.97    145766
   macro avg       0.95      0.98      0.96    145766
weighted avg       0.97      0.97      0.97    145766
```



In [56]:
```
#Storing evaluation metrics (average values)
dt_results = list()
for key in keys:
        dt_results.append(tree.get(key))
dt_results
```

Out[56]:
```
[0.9682642042726013,
 0.9710508060959091,
 0.9682642042726013,
 0.9689886675918266]
```

In [57]:
```
# storing evaluation metrics (per class)
dt_rpf = []
for element in elements:
        dt_rpf.append(tree.get(element))
dt_rpf
```

Out[57]:
```
[array([0.99374204, 0.96881092, 0.91029307, 0.99602912, 0.85779672]),
 array([0.96753004, 0.994     , 0.98225993, 0.99933599, 0.96669483]),
 array([0.98046088, 0.98124383, 0.94490818, 0.99767981, 0.90899588])]
```

In [58]:
```
pickle.dump(search_dt, open('search_dt.p','wb')) # write it as bytes
pickle.dump(dt_model, open('dt_model.p','wb')) # write it as bytes
```

In [59]:
```
# GridSearch using RandomForest is computationally expensive, to save time,

# # Identifying the param_grid to loop through it using GridSearchCV
# param_grid = {'n_estimators':[50,100,200],
#               'criterion':['gini', 'entropy'],
#               'max_features':[2,4,6]}
# model = RandomForestClassifier(random_state = rs, bootstrap = True, class_
# search_rf = GridSearchCV(estimator=model,
#                        param_grid=param_grid,
#                        scoring='accuracy',
#                        cv=kf,
#                        n_jobs = -1) # Initiate search object
```

```
# search_rf.fit(X_train_s, y_train)
# search_rf.best_score_
# search_rf.best_params_
```

In [60]:
```
rf_model = RandomForestClassifier(random_state = rs,
                                  bootstrap = True,
                                  class_weight= class_weight,
                                  criterion = 'gini',
                                  max_depth = 4,
                                  n_estimators = 200)
rf_model.fit(X_train_s,y_train)
```

Out[60]:
```
RandomForestClassifier(class_weight={0: 0.05, 1: 0.3, 2: 0.2, 3: 0.3, 4: 0.1
5},
                       max_depth=4, n_estimators=200, random_state=123)
```

In [61]:
```
preds = rf_model.predict(X_test_s)
randomforest = evaluate_metrics(y_test,preds)
randomforest
```

Out[61]:
```
{'accuracy': 0.9490004527804838,
 'precision': array([0.98890938, 0.99375434, 0.98519128, 0.99274885, 0.77783
821]),
 'Weighted precision': 0.9563683817182562,
 'recall': array([0.9479002 , 0.95466667, 0.92364057, 1.        , 0.9538885
7]),
 'Weighted recall': 0.9490004527804838,
 'f1score': array([0.96797063, 0.97381843, 0.95342357, 0.99636123, 0.8569146
]),
 'Weighted f1score': 0.9509314632166822}
```

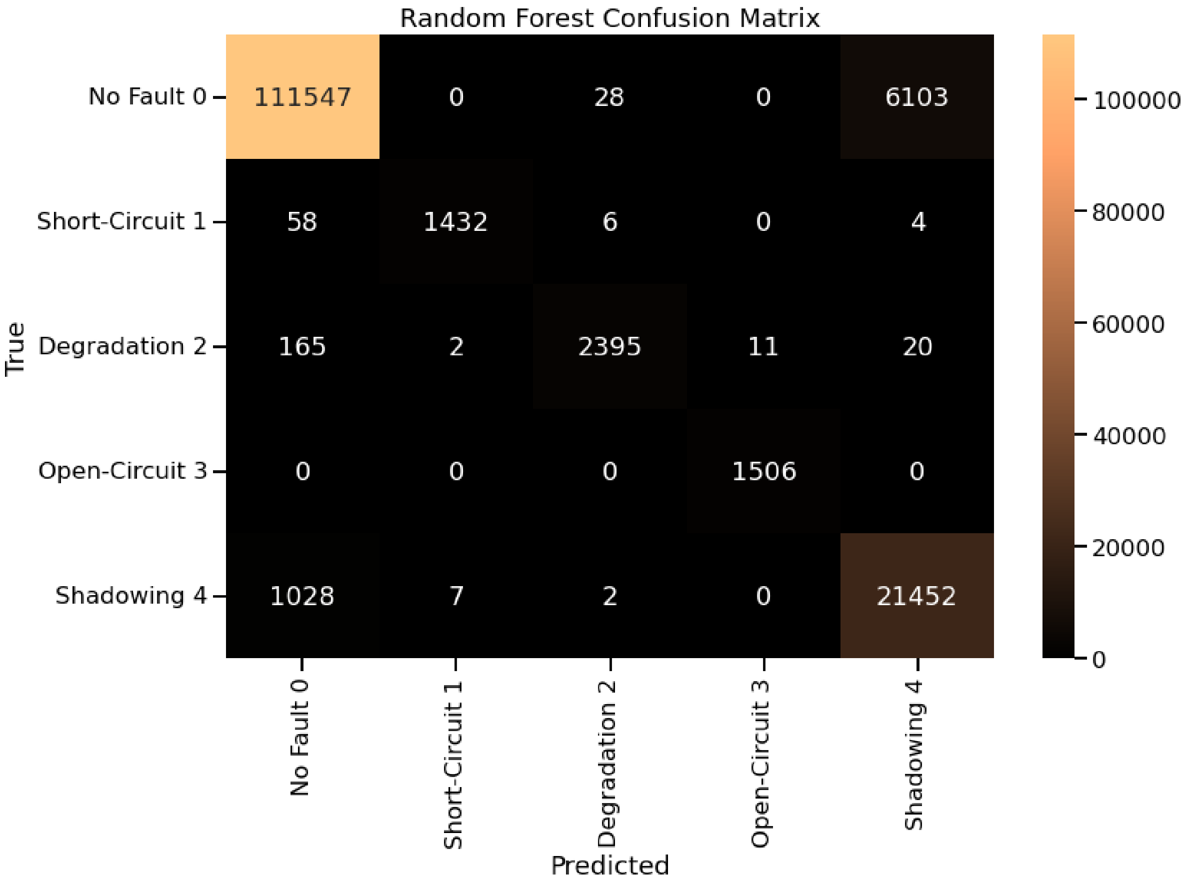
In [62]:
```
print(classification_report(y_test, preds))

sns.set_context('talk')
cm = confusion_matrix(y_test, preds)
plt.figure(figsize = (12,8))
ax = sns.heatmap(cm, annot=True, fmt='d', cmap='copper',
                xticklabels=['No Fault 0', 'Short-Circuit 1', 'Degradation 2
                 yticklabels=['No Fault 0', 'Short-Circuit 1', 'Degradation
ax.set(title="Random Forest Confusion Matrix");
ax.set_xlabel('Predicted');
ax.set_ylabel('True');
```

```
              precision    recall  f1-score   support

           0       0.99      0.95      0.97    117678
           1       0.99      0.95      0.97      1500
           2       0.99      0.92      0.95      2593
           3       0.99      1.00      1.00      1506
           4       0.78      0.95      0.86     22489

    accuracy                           0.95    145766
   macro avg       0.95      0.96      0.95    145766
weighted avg       0.96      0.95      0.95    145766
```



In [63]:
```
#Storing evaluation metrics (average values)
rf_results = list()
for key in keys:
        rf_results.append(randomforest.get(key))
rf_results
```

Out[63]:
```
[0.9490004527804838,
 0.9563683817182562,
 0.9490004527804838,
 0.9509314632166822]
```

In [64]:
```
# storing evaluation metrics (per class)
rf_rpf = []
for element in elements:
        rf_rpf.append(randomforest.get(element))
rf_rpf
```

Out[64]:
```
[array([0.98890938, 0.99375434, 0.98519128, 0.99274885, 0.77783821]),
 array([0.9479002 , 0.95466667, 0.92364057, 1.        , 0.95388857]),
 array([0.96797063, 0.97381843, 0.95342357, 0.99636123, 0.8569146 ])]
```

In [65]:
```
# pickle.dump(search_rf, open('search_rf.p','wb')) # write it as bytes
pickle.dump(rf_model, open('rf_model.p','wb')) # write it as bytes
```

In [66]:
```
final_results= {
    'Metric': ['Accuracy',' Weighted Precision','Weighted Recall','Weighted
    'Logistic Regression' :lr_results,
    'Decision Tree'       :dt_results,
    'Random Forest'      :rf_results}
final_results = pd.DataFrame(final_results).set_index('Metric')
display(final_results)
```

Metric	Logistic Regression	Decision Tree	Random Forest
Accuracy	0.924619	0.968264	0.949000
Weighted Precision	0.921286	0.971051	0.956368
Weighted Recall	0.924619	0.968264	0.949000
Weighted F1score	0.919966	0.968989	0.950931

In [68]:
```
final_results_per_class = {
    'classes': [0,1,2,3,4],
    'LR Precision' :lr_rpf[0],
    'LR Recall' :lr_rpf[1],
    'LR F1score' :lr_rpf[2],
    'DT Precision':dt_rpf[0],
    'DT Recall':dt_rpf[1],
    'DT F1 score':dt_rpf[2],
    'RF recall':rf_rpf[0],
    'RF precision':rf_rpf[1],
    'RF F1 score':rf_rpf[2]}
final_results_per_class = pd.DataFrame(final_results_per_class).set_index('c
final_results_per_class.T
```

Out[68]:

classes	0	1	2	3	4
LR Precision	0.932310	0.985469	0.975090	0.992749	0.848332
LR Recall	0.979053	0.994667	0.935981	1.000000	0.628752
LR F1score	0.955110	0.990046	0.955136	0.996361	0.722221
DT Precision	0.993742	0.968811	0.910293	0.996029	0.857797
DT Recall	0.967530	0.994000	0.982260	0.999336	0.966695
DT F1 score	0.980461	0.981244	0.944908	0.997680	0.908996
RF recall	0.988909	0.993754	0.985191	0.992749	0.777838
RF precision	0.947900	0.954667	0.923641	1.000000	0.953889
RF F1 score	0.967971	0.973818	0.953424	0.996361	0.856915

3 - Key Findings

A - The dataset is extremely skewed toward 'no fault'.
B - Decision Tree and Random Forest models performed very well in the validation set.
C - In terms of performance, Decision Tree is the best algorithm to use, then Random Forest, and lastly Logistic Regression.

4 - Possible Flaws & Suggestions for Future Work

A - Reweighting was the best option to deal with the imbalanced data. However, there might be a room for rebalancing improvement.
B - Logistic Regression model has a problem identifying class '4', because class '4' has a recall of 0.63 only.
C - The frequency of measuring the PV panels attributes can be adjusted. Because

within 16 days they measured 1,373,798 times, i.e., one measurement every second. Although it is adapting real-life scenarios, I recommend to reduce the capturing frequency to avoid plateauing the dataset with no fault status. if measurements are taken every two seconds, the dataset size will be reduced into half and same goal can be acheived.
D - The major confusion is between class 0 and 4.

References

[1] Lazzaretti, A. E., Costa, C. H. D., Rodrigues, M. P., Yamada, G. D., Lexinoski, G., Moritz, G. L., Oroski, E., Goes, R. E. D., Linhares, R. R., Stadzisz, P. C., Omori, J. S., & Santos, R. B. D. (2020). A Monitoring System for Online Fault Detection and Classification in Photovoltaic Plants. Sensors, 20(17), 4688. https://doi.org/10.3390/s20174688 dataset link : https://github.com/clayton-h-costa/pv_fault_dataset