Roddsi Sarkar (UIN - 334003075)

Problem Introduction

Energy transition, wherein countries are preparing to shift from fossil based energy to renewable sources of energy in the modern world requires dependence on local weather and geographic conditions. In this analysis and study, our main objective is to understand how extreme weather events impact performance of the photovoltaic plants in several regions of the United States.The idea is that if we can do this analysis for the US, we can also extend it to other countries and better understand and facilitate renewable energy generation given the weather patterns and events are vastly different across countries and geographies. We perform statistical learning techniques like Regression and classification to predict the performance and irradiation values given the measurements above.

For this analysis, we have used 2 regression techniques - using Ordinary Least Squares and its variation Ridge regression to predict "PR" and 2 classification techniques - Random Forest classifier and Decision tree classifier to predict "low_irradiation". I have used the sklearn library.

Data Set Information

We have data available from 3 primary sources - measurements of extreme weather conditions, plant production data and operation and maintenance tickets. Not all of these data is useful as some contains unwanted noise which may have been introduced during incorrect recording of data or missing data. There are a total of 51504 observations and 38 variables out of which "PR" and "low_irradiation" will be our two target/response variables and some combination of the others will be considered as predictors. Simply put, PR/Performance ratio captures the energy losses while irradiation is in the context of solar irradiance where higher the irradiance, greater is the output solar energy. Plant production data includes parameters like "hurr_production_level"; operation and maintenenance tickets includes data like "snow_bin_ticket_minutes" and lastly, an example of extreme weather conditions would be "cumulative_snow_mm".

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

In [2]:
```
#Loading the dataset
energydata = pd.read_csv('energydata.csv')
```

Proposed Approach/Methodology

First, I will be viewing the dataset and see if there are any strong correlations among variables. If there are misisng data, I will deal with that using some method of imputation separately for numeric and categorical data. Next, I will perform 2 classification techniques and 2 regression techniques to predict "PR" and "low_irradiation" respectively given some non trivial combination of the predictors.We will see how the models perform and evaluate them. Lastly, I will discuss the limitations of this stud and analysis and scope out any future improvements.

#Viewing the Energy dataset

We check the shape of the dataset to get a sense of the size of the dataset we will be analyzing. We see there are 51504 rows and 38 columns.

In [3]:
```
#checking the shape of the dataset
energydata.shape
```

Out[3]:
```
(51504, 38)
```

We print the first and last 5 rows of the dataset and look at the values. The data appears sorted in some manner (realized it is time series) which leads us to think that w:e might need to split randomly into train and test datasets when we implement statistical learning techniques to analyze the data in order to count in the variability.

In [4]:
```
# Print the first 5 records.
print(energydata.head())
```

```
  randid      Date NOAAClimRegion TempZone HumidZone bin_PlantSize_kW  \
0   C2S1  4/1/2018           West       T6        H4            large
1   C2S1  4/2/2018           West       T6        H4            large
2   C2S1  4/3/2018           West       T6        H4            large
3   C2S1  4/4/2018           West       T6        H4            large
4   C2S1  4/5/2018           West       T6        H4            large

   plant_age_months active_snow_tickets snow_bin_ticket_minutes  \
0              19.0                  No                    None
1              19.0                  No                    None
2              19.0                  No                    None
3              19.0                  No                    None
4              19.0                  No                    None

  snow_affected_assets  ... storm_affected_assets  storm_production_level
\
0                 None  ...                  None                 Unknown
1                 None  ...                  None                 Unknown
2                 None  ...                  None                 Unknown
3                 None  ...                  None                 Unknown
4                 None  ...                  None                 Unknown

   lightning  storm  duration_minutes_storm  nearest_storm flood  \
0          0    0.0                       0           2420   0.0
1          0    0.0                       0           2420   0.0
2          0    0.0                       0           2420   0.0
3          0    0.0                       0           2420   0.0
4          0    0.0                       0           2420   0.0

  duration_minutes_flood nearest_flood rain
0                      0          2255  0.0
1                      0          2255  0.0
2                      0          2255  0.0
3                      0          2255  0.0
4                      0          2255  0.0

[5 rows x 38 columns]
```

In [ ]:
```
# Print the last 5 records.
print(energydata.tail())
```

```
      randid       Date NOAAClimRegion TempZone HumidZone bin_PlantSize_kW
\
51499  C3S40  7/27/2019      Southeast       T5        H4           medium
51500  C3S40  7/28/2019      Southeast       T5        H4           medium
51501  C3S40  7/29/2019      Southeast       T5        H4           medium
51502  C3S40  7/30/2019      Southeast       T5        H4           medium
51503  C3S40  7/31/2019      Southeast       T5        H4           medium

       plant_age_months active_snow_tickets snow_bin_ticket_minutes  \
51499              31.0                  No                    None
51500              31.0                  No                    None
51501              31.0                  No                    None
51502              31.0                  No                    None
51503              31.0                  No                    None

      snow_affected_assets  ... storm_affected_assets  storm_production_le
vel  \
51499                 None  ...                  None                 Unkn
own
51500                 None  ...                  None                 Unkn
own
51501                 None  ...                  None                 Unkn
own
51502                 None  ...                  None                 Unkn
own
51503                 None  ...                  None                 Unkn
own

       lightning  storm  duration_minutes_storm  nearest_storm flood  \
51499          0    0.0                       0             57   0.0
51500          0    0.0                       0             58   0.0
51501          0    0.0                       0             59   0.0
51502          0    0.0                       0             60   0.0
51503          0    0.0                       0             61   0.0

      duration_minutes_flood nearest_flood rain
51499                      0           315  0.0
51500                      0           316  0.0
51501                      0           317  0.0
51502                      0           318  0.0
51503                      0           319  0.0

[5 rows x 38 columns]
```

Next, we look at the dataset and observe that there are 13 columns with missing values in some rows. Out of these 13, we have 5 numerical and 8 categorical columns with missing data. (**Note - The 0s and 1s have been erroneously categorised as numerical even though they are categorical data. Hence, we see the discrepancy in the count value of datatypes.**)

In [ ]:
```
energydata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51504 entries, 0 to 51503
Data columns (total 38 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   randid                     51504 non-null  object 
 1   Date                       51504 non-null  object 
 2   NOAAClimRegion             51504 non-null  object 
 3   TempZone                   51504 non-null  object 
 4   HumidZone                  51504 non-null  object 
 5   bin_PlantSize_kW           51504 non-null  object 
 6   plant_age_months           51356 non-null  float64
 7   active_snow_tickets        51504 non-null  object 
 8   snow_bin_ticket_minutes    51504 non-null  object 
 9   snow_affected_assets       51504 non-null  object 
 10  snow_production_level      51437 non-null  object 
 11  PR                         49940 non-null  float64
 12  snow_value_mm              45682 non-null  float64
 13  total_daily_snow_mm        45327 non-null  float64
 14  low_irradiation            51504 non-null  int64  
 15  cumulative_snow_mm         39226 non-null  float64
 16  hurr_bin_ticket_minutes    51504 non-null  object 
 17  hurr_affected_assets       51504 non-null  object 
 18  hurr_production_level      51487 non-null  object 
 19  HurricanePrep              51504 non-null  object 
 20  HurricanePostInspection    51504 non-null  object 
 21  hurricane                  45753 non-null  float64
 22  nearest_hurricane          51504 non-null  int64  
 23  wind_speed_mean            51504 non-null  object 
 24  rain_value_mm              40703 non-null  float64
 25  nearest_rain               51504 non-null  int64  
 26  storm_active_tickets       51504 non-null  object 
 27  storm_bin_ticket_minutes   51504 non-null  object 
 28  storm_affected_assets      51504 non-null  object 
 29  storm_production_level     51446 non-null  object 
 30  lightning                  51504 non-null  int64  
 31  storm                      45753 non-null  float64
 32  duration_minutes_storm     51504 non-null  int64  
 33  nearest_storm              51504 non-null  int64  
 34  flood                      45753 non-null  float64
 35  duration_minutes_flood     51504 non-null  int64  
 36  nearest_flood              51504 non-null  int64  
 37  rain                       40703 non-null  float64
dtypes: float64(10), int64(8), object(20)
memory usage: 14.9+ MB
```

We check the percentage of missing values to see if we need to deal with the data or we can ignore and just drop the columns. For instance, the missing values percentage for column "plant_age_months" is just 0.28 which is why we might consider using a mean imputation method as opposed to column "cumulative_snow_mm" which is 23.838 (comparatively high) and may need to impute missing data via less biased imputation methods. So far, none of the columns have very high missing data, therefore we need not drop columns. **For the sake of simplicity, we will impute the numerical data with their median values**

In [ ]:
```
energydata.isnull().sum() / energydata.shape[0] * 100
```

Out[78]:
```
randid                       0.000000
Date                         0.000000
NOAAClimRegion               0.000000
TempZone                     0.000000
HumidZone                    0.000000
bin_PlantSize_kW             0.000000
plant_age_months             0.287356
active_snow_tickets          0.000000
snow_bin_ticket_minutes      0.000000
snow_affected_assets         0.000000
snow_production_level        0.130087
PR                           3.036657
snow_value_mm               11.303976
total_daily_snow_mm         11.993243
low_irradiation              0.000000
cumulative_snow_mm          23.838925
hurr_bin_ticket_minutes      0.000000
hurr_affected_assets         0.000000
hurr_production_level        0.033007
HurricanePrep                0.000000
HurricanePostInspection      0.000000
hurricane                   11.166123
nearest_hurricane            0.000000
wind_speed_mean              0.000000
rain_value_mm               20.971187
nearest_rain                 0.000000
storm_active_tickets         0.000000
storm_bin_ticket_minutes     0.000000
storm_affected_assets        0.000000
storm_production_level       0.112613
lightning                    0.000000
storm                       11.166123
duration_minutes_storm       0.000000
nearest_storm                0.000000
flood                       11.166123
duration_minutes_flood       0.000000
nearest_flood                0.000000
rain                        20.971187
dtype: float64
```

Splitting the dataset and storing numerical and categorical variables separately:

We need to take note that low_irradiation variable is a binary variable and therefore the number of numerical features will be 17.

In [5]:
```
#numerical features
numerical_data = energydata.select_dtypes(include='number')
numerical_features=numerical_data.columns.tolist()

print(f'There are {len(numerical_features)} numerical features:', '\n')
print(numerical_features)
```

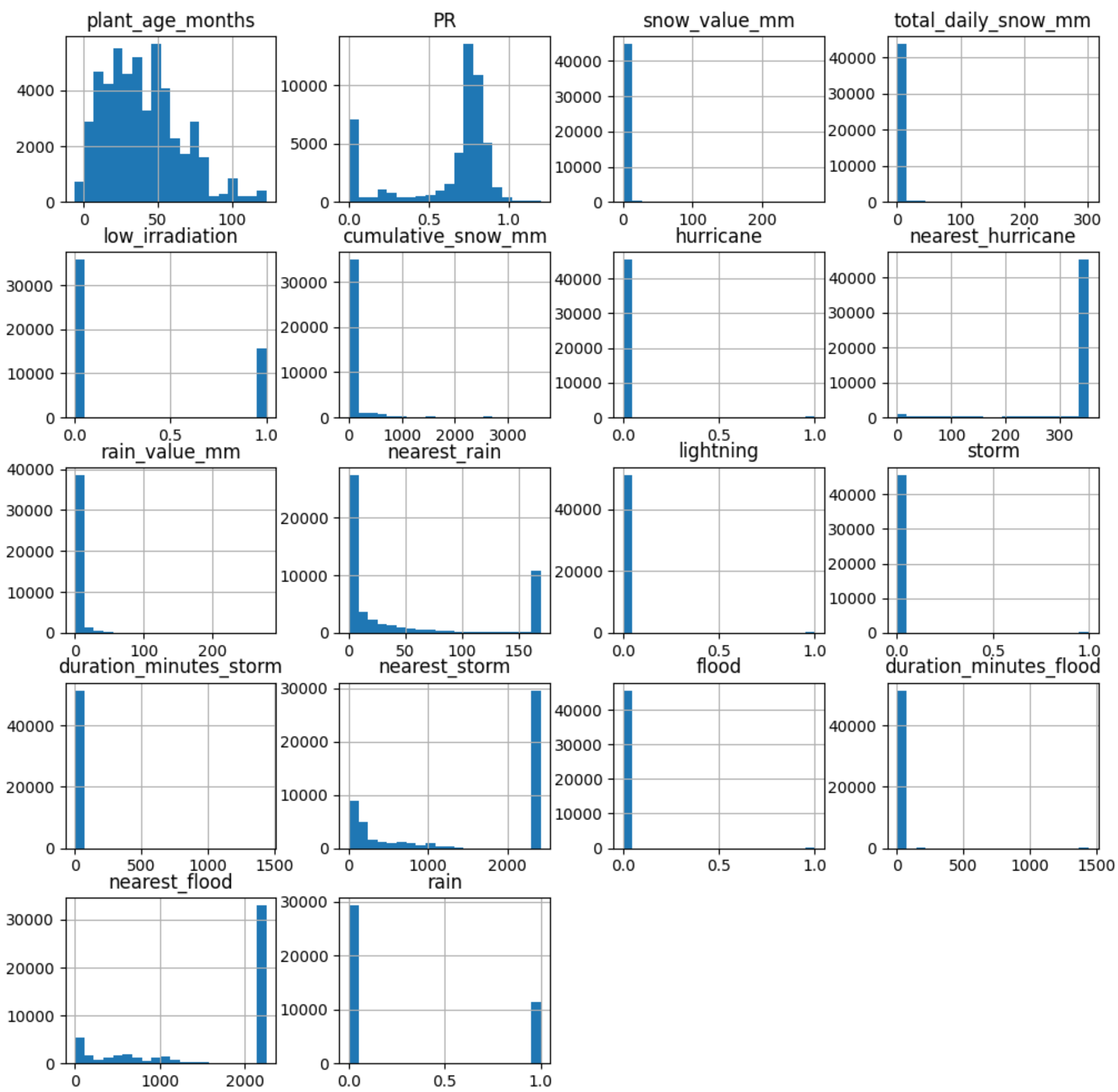
```
There are 18 numerical features:

['plant_age_months', 'PR', 'snow_value_mm', 'total_daily_snow_mm', 'low_ir
radiation', 'cumulative_snow_mm', 'hurricane', 'nearest_hurricane', 'rain_
value_mm', 'nearest_rain', 'lightning', 'storm', 'duration_minutes_storm',
'nearest_storm', 'flood', 'duration_minutes_flood', 'nearest_flood', 'rai
n']
```

In [6]:
```
#Summary statistics of numerical features
numerical_data.describe().T
```

Out[6]:

	count	mean	std	min	25%	50%
plant_age_months	51356.0	39.707726	25.254713	-6.0	20.000000	36.000000
PR	49940.0	0.623206	0.299353	0.0	0.586168	0.753464
snow_value_mm	45682.0	1.257194	10.556568	0.0	0.000000	0.000000
total_daily_snow_mm	45327.0	2.927878	17.889680	0.0	0.000000	0.000000
low_irradiation	51504.0	0.305297	0.460537	0.0	0.000000	0.000000
cumulative_snow_mm	39226.0	105.063318	396.042228	0.0	0.000000	0.000000
hurricane	45753.0	0.007082	0.083854	0.0	0.000000	0.000000
nearest_hurricane	51504.0	328.895018	77.013566	0.0	354.000000	354.000000
rain_value_mm	40703.0	2.302144	8.147026	0.0	0.000000	0.000000
nearest_rain	51504.0	46.778444	66.988867	0.0	1.000000	6.000000
lightning	51504.0	0.007184	0.084454	0.0	0.000000	0.000000
storm	45753.0	0.003978	0.062946	0.0	0.000000	0.000000
duration_minutes_storm	51504.0	0.408745	18.914858	0.0	0.000000	0.000000
nearest_storm	51504.0	1519.576460	1070.425033	0.0	206.000000	2420.000000
flood	45753.0	0.001530	0.039085	0.0	0.000000	0.000000
duration_minutes_flood	51504.0	0.606458	25.353251	0.0	0.000000	0.000000
nearest_flood	51504.0	1624.949984	877.195268	0.0	700.000000	2255.000000
rain	40703.0	0.281011	0.449498	0.0	0.000000	0.000000

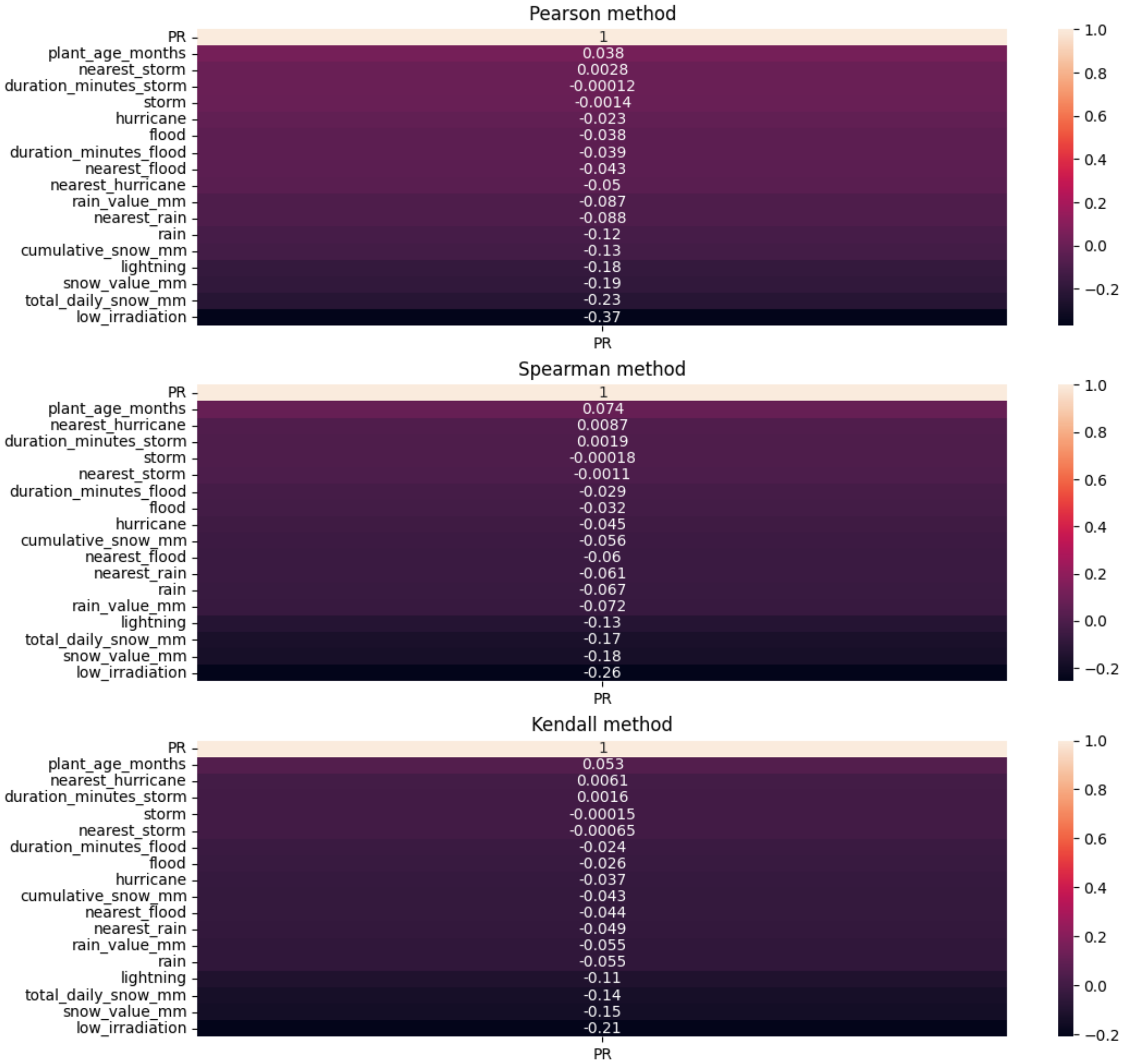
In [ ]:
```
numerical_data.hist(figsize=(12,12),bins=20)
plt.show()
```



We try to see if repsonse variable "PR" is strongly correlated with the predictor variables and observe from the below plots that all **these numerical predictors show very little correlation with PR**. We have used 3 different correlation methods - pearson, spearman and kendall.

In [7]:
```
import seaborn as sb
import matplotlib.pyplot as plt
```

In [8]:
```
fig, ax = plt.subplots(3,1, figsize=(12, 12))
corr1 = numerical_data.corr('pearson')[['PR']].sort_values(by='PR', ascendi
corr2 = numerical_data.corr('spearman')[['PR']].sort_values(by='PR', ascend
corr3 = numerical_data.corr('kendall')[['PR']].sort_values(by='PR', ascendi

ax[0].set_title('Pearson')
ax[1].set_title('Spearman')
ax[2].set_title('Kendall')

sb.heatmap(corr1, ax=ax[0], annot=True)
sb.heatmap(corr2, ax=ax[1], annot=True)
sb.heatmap(corr3, ax=ax[2], annot=True)

plt.show()
```



Reiterating the fact that low_irradiation is a binary variable and not a numerical variable with values 0 and 1 as depicted.

In [9]:
```
#categoricalfeatures
categorical_data=energydata.select_dtypes(include= 'object')
categorical_features=categorical_data.columns.tolist()

print(f'There are {len(categorical_features)} numerical features:', '\n')
print(categorical_features)
```

```
There are 20 numerical features:

['randid', 'Date', 'NOAAClimRegion', 'TempZone', 'HumidZone', 'bin_PlantSize_kW', 'active_snow_tickets', 'snow_bin_ticket_minutes', 'snow_affected_assets', 'snow_production_level', 'hurr_bin_ticket_minutes', 'hurr_affected_assets', 'hurr_production_level', 'HurricanePrep', 'HurricanePostInspection', 'wind_speed_mean', 'storm_active_tickets', 'storm_bin_ticket_minutes', 'storm_affected_assets', 'storm_production_level']
```

In [10]:
```
#Summary statistics of categorical features
categorical_data.describe(include='object').T
```

Out[10]:

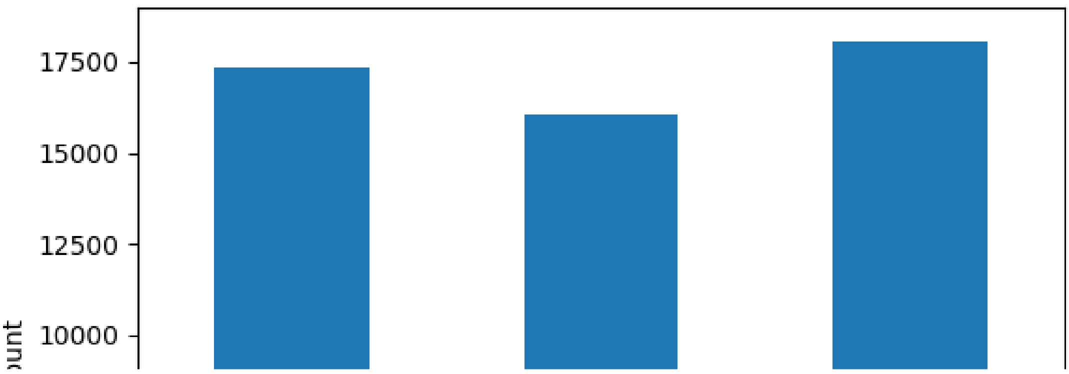
	count	unique	top	freq
randid	51504	174	C3S33	739
Date	51504	739	3/1/2019	171
NOAAClimRegion	51504	9	West	23915
TempZone	51504	5	T5	23465
HumidZone	51504	4	H4	46103
bin_PlantSize_kW	51504	3	small	18083
active_snow_tickets	51504	2	No	50714
snow_bin_ticket_minutes	51504	3	None	50714
snow_affected_assets	51504	7	None	50714
snow_production_level	51437	3	Unknown	50714
hurr_bin_ticket_minutes	51504	3	None	51035
hurr_affected_assets	51504	5	None	51035
hurr_production_level	51487	3	Unknown	51035
HurricanePrep	51504	2	No	51339
HurricanePostInspection	51504	2	No	51414
wind_speed_mean	51504	33670	#NUM!	11167
storm_active_tickets	51504	2	No	50956
storm_bin_ticket_minutes	51504	3	None	50956
storm_affected_assets	51504	8	None	50956
storm_production_level	51446	3	Unknown	50956

In [11]:
```
# unique values counts, enumerate function usage referenced from lab walk t
unique_counts=categorical_data.nunique()

for index,i in enumerate(range(7),start=1):
    print(index,"{a} has {b} unique values".format(a=categorical_features[i
```

```
1 randid has 174 unique values
2 Date has 739 unique values
3 NOAAClimRegion has 9 unique values
4 TempZone has 5 unique values
5 HumidZone has 4 unique values
6 bin_PlantSize_kW has 3 unique values
7 active_snow_tickets has 2 unique values
```

In [26]:
```
for col in categorical_features:
    print()
    print(f"\033[1m{col}\033[0m\n")
    categorical_data[col].value_counts().sort_index().plot(kind='bar', rot=
    plt.show()
```

bin_PlantSize_kW



We see that most of the features are unbalanced except for a few like bin_PlantSize_kW, TempZone etc.

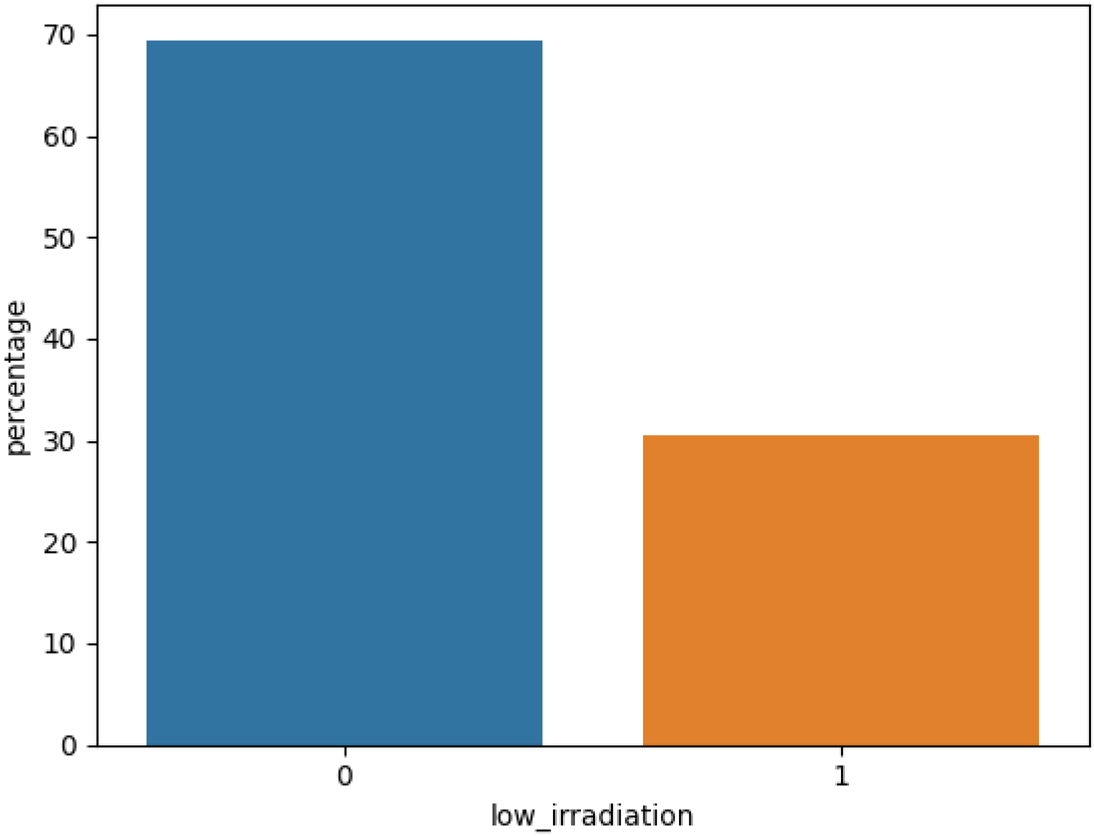
However, we are interested to see the imbalance in the target/response variable low_irradiation" to understand which performance metrices like accuracy, recall and precision might be a better choice to evaluate model. From below result it is evident that there is imbalance between two classes (approx 40%).

In [13]:
```
class_counts=energydata.groupby("low_irradiation").size()

columns=['low_irradiation','count','percentage']
low_irradiation=[0,1]
count=list()
percentage=list()

for val in range(2):
    count.append(class_counts[val])
    percent=(class_counts[val]/51504)*100
    percentage.append(percent)

imbalance=pd.DataFrame(list(zip(low_irradiation,count,percentage)),columns=
imbalance
```

Out[13]:

	low_irradiation	count	percentage
0	0	35780	69.470332
1	1	15724	30.529668

In [14]:
```
sb.barplot(data=imbalance,x=imbalance['low_irradiation'],y=imbalance['perce
plt.show()
```



Now, let's impute missing values. Reference - [https://jamesrledoux.com/code/imputation (https://jamesrledoux.com/code/imputation)](https://jamesrledoux.com/code/imputation)

In [15]:
```
#Median imputation for numerical variables
#energydata_median_imputed = energydata.fillna(energydata.median())
energydata['PR'] = energydata['PR'].fillna(energydata['PR'].median())
energydata['snow_value_mm'] = energydata['snow_value_mm'].fillna(energydata
energydata['total_daily_snow_mm'] = energydata['total_daily_snow_mm'].filln
energydata['cumulative_snow_mm'] = energydata['cumulative_snow_mm'].fillna(
energydata['rain_value_mm'] = energydata['rain_value_mm'].fillna(energydata
energydata['plant_age_months'] = energydata['plant_age_months'].fillna(ener
energydata
```

Out[15]:

	randid	Date	NOAAClimRegion	TempZone	HumidZone	bin_PlantSize_kW	plant_
0	C2S1	4/1/2018	West	T6	H4	large	
1	C2S1	4/2/2018	West	T6	H4	large	
2	C2S1	4/3/2018	West	T6	H4	large	
3	C2S1	4/4/2018	West	T6	H4	large	
4	C2S1	4/5/2018	West	T6	H4	large	
...	...	...	...	...	...	...	
51499	C3S40	7/27/2019	Southeast	T5	H4	medium	
51500	C3S40	7/28/2019	Southeast	T5	H4	medium	
51501	C3S40	7/29/2019	Southeast	T5	H4	medium	
51502	C3S40	7/30/2019	Southeast	T5	H4	medium	
51503	C3S40	7/31/2019	Southeast	T5	H4	medium	

51504 rows × 38 columns

In [16]:
```
energydata.isnull().sum()
```

Out[16]:
```
randid                         0
Date                           0
NOAAClimRegion                 0
TempZone                       0
HumidZone                      0
bin_PlantSize_kW               0
plant_age_months               0
active_snow_tickets            0
snow_bin_ticket_minutes        0
snow_affected_assets           0
snow_production_level         67
PR                             0
snow_value_mm                  0
total_daily_snow_mm            0
low_irradiation                0
cumulative_snow_mm             0
hurr_bin_ticket_minutes        0
hurr_affected_assets           0
hurr_production_level         17
HurricanePrep                  0
HurricanePostInspection        0
hurricane                   5751
nearest_hurricane              0
wind_speed_mean                0
rain_value_mm                  0
nearest_rain                   0
storm_active_tickets           0
storm_bin_ticket_minutes       0
storm_affected_assets          0
storm_production_level        58
lightning                      0
storm                       5751
duration_minutes_storm         0
nearest_storm                  0
flood                       5751
duration_minutes_flood         0
nearest_flood                  0
rain                       10801
dtype: int64
```

In [17]:
```
#Imputing the following variables with mode even though "rain", "storm", "f

mode_value_rain = energydata['rain'].mode()[0]
energydata['rain'].fillna(mode_value_rain, inplace=True)

mode_value_flood = energydata['flood'].mode()[0]
energydata['flood'].fillna(mode_value_flood, inplace=True)

mode_value_storm = energydata['storm'].mode()[0]
energydata['storm'].fillna(mode_value_storm, inplace=True)

mode_value_hurricane = energydata['hurricane'].mode()[0]
energydata['hurricane'].fillna(mode_value_hurricane, inplace=True)

energydata
```

Out[17]:

	randid	Date	NOAAClimRegion	TempZone	HumidZone	bin_PlantSize_kW	plant_
0	C2S1	4/1/2018	West	T6	H4	large	
1	C2S1	4/2/2018	West	T6	H4	large	
2	C2S1	4/3/2018	West	T6	H4	large	
3	C2S1	4/4/2018	West	T6	H4	large	
4	C2S1	4/5/2018	West	T6	H4	large	
...	...	...	...	...	...	...	
51499	C3S40	7/27/2019	Southeast	T5	H4	medium	
51500	C3S40	7/28/2019	Southeast	T5	H4	medium	
51501	C3S40	7/29/2019	Southeast	T5	H4	medium	
51502	C3S40	7/30/2019	Southeast	T5	H4	medium	
51503	C3S40	7/31/2019	Southeast	T5	H4	medium	

51504 rows × 38 columns

In [18]:
```
#verifying the dataset
energydata.isnull().sum()
```

Out[18]:
```
randid                     0
Date                       0
NOAAClimRegion             0
TempZone                   0
HumidZone                  0
bin_PlantSize_kW           0
plant_age_months           0
active_snow_tickets        0
snow_bin_ticket_minutes    0
snow_affected_assets       0
snow_production_level     67
PR                         0
snow_value_mm              0
total_daily_snow_mm        0
low_irradiation            0
cumulative_snow_mm         0
hurr_bin_ticket_minutes    0
hurr_affected_assets       0
hurr_production_level     17
HurricanePrep              0
HurricanePostInspection    0
hurricane                  0
nearest_hurricane          0
wind_speed_mean            0
rain_value_mm              0
nearest_rain               0
storm_active_tickets       0
storm_bin_ticket_minutes   0
storm_affected_assets      0
storm_production_level    58
lightning                  0
storm                      0
duration_minutes_storm     0
nearest_storm              0
flood                      0
duration_minutes_flood     0
nearest_flood              0
rain                       0
dtype: int64
```

Analyzing the Dataset

Now that we have viewed the dataset, we would predict the "PR" and "low_irradiation" using different regression and classification techniques based on some combination of the dataset.

Regression Techniques

1. Multiple Linear regression using OLS

In [19]:
```
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

In [20]:
```
#Extracting day, month and year from "Date"" into columns
#Reference  - https://sparkbyexamples.com/pandas/pandas-get-day-month-and-y
energydata["Date"]= pd.to_datetime(energydata[ "Date"])
energydata['Day']=energydata[ "Date"].dt.day
energydata["Date"]= pd.to_datetime(energydata[ "Date"])
energydata['Month']=energydata[ "Date"].dt.month
energydata["Date"]= pd.to_datetime(energydata[ "Date"])
energydata['Year']=energydata[ "Date"].dt.year
energydata
```

Out[20]:

	randid	Date	NOAAClimRegion	TempZone	HumidZone	bin_PlantSize_kW	plant_age
0	C2S1	2018-04-01	West	T6	H4	large	
1	C2S1	2018-04-02	West	T6	H4	large	
2	C2S1	2018-04-03	West	T6	H4	large	
3	C2S1	2018-04-04	West	T6	H4	large	
4	C2S1	2018-04-05	West	T6	H4	large	
...	...	...	...	...	...	...	
51499	C3S40	2019-07-27	Southeast	T5	H4	medium	
51500	C3S40	2019-07-28	Southeast	T5	H4	medium	
51501	C3S40	2019-07-29	Southeast	T5	H4	medium	
51502	C3S40	2019-07-30	Southeast	T5	H4	medium	
51503	C3S40	2019-07-31	Southeast	T5	H4	medium	

51504 rows × 41 columns

In [ ]:
```
#Reference used -  https://stackoverflow.com/questions/13610074/is-there-a-
y=energydata['PR']
X=energydata[['Day','Month','Year','plant_age_months','snow_value_mm','tota
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.2,
                                                    random_state=42)
```

In [ ]:
```
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[121]:
```
LinearRegression()
```

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In [ ]:
```
feature_names = X.columns
model_coefficients = regressor.coef_

coefficients = pd.DataFrame(data = model_coefficients,
                              index = feature_names,
                              columns = ['Coefficient value'])
print(coefficients)
```

```
                       Coefficient value
Day                             0.000306
Month                          -0.008335
Year                           -0.070495
plant_age_months                0.000453
snow_value_mm                  -0.001584
total_daily_snow_mm            -0.002572
cumulative_snow_mm             -0.000024
hurricane                      -0.122258
nearest_hurricane              -0.000193
rain_value_mm                  -0.001329
nearest_rain                   -0.000417
lightning                      -0.586387
storm                          -0.005993
duration_minutes_storm          0.000046
nearest_storm                   0.000022
flood                          -0.082986
duration_minutes_flood         -0.000368
nearest_flood                  -0.000016
rain                           -0.035579
```

Interpretation of the coefficients - For a unit increase in lightning, PR decreases by 0.586387 units and for a unit increase in plant_age_months, PR increases by 0.00453 and so on. We can observe from the above list that lightning, hurricane, flood have the highest impact comparatively although in absolute values, these are **not the strongest correlations**.

Now, we make predictions with the above model.

In [ ]:
```
y_pred = regressor.predict(X_test)
results = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
print(results)
```

```
         Actual  Predicted
543    0.774798   0.715872
23967  0.708579   0.633685
41770  0.618758   0.563343
22060  0.600001   0.584669
11429  0.000000   0.670338
...         ...        ...
44668  0.789966   0.633018
15353  0.730838   0.651973
2237   0.827550   0.680665
45045  0.873304   0.613330
23144  0.826519   0.606705

[10301 rows x 2 columns]
```

Evaluating the model

In [ ]:
```
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
```

In [ ]:
```
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)

print(f'Mean absolute error: {mae:.2f}')
print(f'Mean squared error: {mse:.2f}')
print(f'Root mean squared error: {rmse:.2f}')
```

```
Mean absolute error: 0.21
Mean squared error: 0.08
Root mean squared error: 0.28
```

The mae score of 0.21 seems good but we need to figure out if this is consistent across the dataset.

In [ ]:
```
regressor.score(X_test, y_test)  #R squared value
```

Out[107]:
```
0.08795469670310885
```

The model explains only 8.8% of the test data which is a very poor result. Let's see for our training data.

In [ ]:
```
regressor.score(X_train, y_train)
```

Out[108]:
```
0.10540610732176614
```

The model explains only 10.54% of the training data which is again a poor result.

In [ ]:
```
#Reference used - https://www.statology.org/k-fold-cross-validation-in-pyth

from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
import statistics

#defined the cross-validation method that we will use
cv = KFold(n_splits=10, random_state=1, shuffle=True)

#build multiple linear regression model
model = LinearRegression()

#use k-fold CV to evaluate model
scores = cross_val_score(model, X, y, scoring='neg_mean_absolute_error',
                         cv=cv, n_jobs=-1)
statistics.mean(abs(scores))
```

Out[109]:
```
0.21230124578395682
```

Cross validation using kfold gives us the score as 0.2123 which is again very poor. We will next try to analyze using a variant of OLS, the ridge regression and see if there is any improvement.

When it comes to model interpretability, I don't think the model is interpretable as the MAE is only 0.21 and we are able to explain a very low percentage of the dataset, both training and testing.

2. Ridge regression

In [ ]:
```
#cross validation using k fold
from sklearn.linear_model import Ridge
from numpy import mean
from numpy import std
from numpy import absolute

cv = KFold(n_splits=10, random_state=1, shuffle=True)
model = Ridge(alpha=1.0)

scores = cross_val_score(model, X, y, scoring='neg_mean_absolute_error', cv
scores = abs(scores)
print('Mean MAE: %.3f (%.3f)' % (mean(scores), std(scores)))
```

```
Mean MAE: 0.212 (0.003)
```

In [ ]:
```
X_train1, X_test1, y_train1, y_test1 = train_test_split(X, y,
                                                    test_size=0.2,
                                                    random_state=42)
```

In [ ]:
```
model1 = Ridge(alpha=1.0)
model1.fit(X_train1, y_train1)
```

Out[112]:
```
Ridge()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [ ]:
```
feature_names1 = X.columns
model_coefficients1 = model1.coef_

coefficients1 = pd.DataFrame(data = model_coefficients1,
                              index = feature_names1,
                              columns = ['Coefficient value'])
print(coefficients1)
```

```
                        Coefficient value
Day                              0.000306
Month                           -0.008336
Year                            -0.070499
plant_age_months                 0.000453
snow_value_mm                   -0.001584
total_daily_snow_mm             -0.002572
cumulative_snow_mm              -0.000024
hurricane                       -0.121700
nearest_hurricane               -0.000193
rain_value_mm                   -0.001331
nearest_rain                    -0.000417
lightning                       -0.584418
storm                           -0.005940
duration_minutes_storm           0.000046
nearest_storm                    0.000022
flood                           -0.080717
duration_minutes_flood          -0.000370
nearest_flood                   -0.000016
rain                            -0.035573
```

In [ ]:
```
y_pred1 = model1.predict(X_test1)
results2 = pd.DataFrame({'Actual': y_test1, 'Predicted': y_pred1})
print(results2)
```

```
         Actual  Predicted
543    0.774798   0.715868
23967  0.708579   0.633651
41770  0.618758   0.563272
22060  0.600001   0.584623
11429  0.000000   0.670330
...         ...        ...
44668  0.789966   0.633022
15353  0.730838   0.651947
2237   0.827550   0.680645
45045  0.873304   0.613357
23144  0.826519   0.606697

[10301 rows x 2 columns]
```

We don't see much difference in the values predicted when compared to linear regression using OLS.

In [ ]:
```
mae1 = mean_absolute_error(y_test1, y_pred1)
mse1 = mean_squared_error(y_test1, y_pred1)
rmse1 = np.sqrt(mse1)

print(f'Mean absolute error: {mae1:.2f}')
print(f'Mean squared error: {mse1:.2f}')
print(f'Root mean squared error: {rmse1:.2f}')
```

```
Mean absolute error: 0.21
Mean squared error: 0.08
Root mean squared error: 0.28
```

In [ ]:
```
model1.score(X_test1, y_test1)  #R squared value
```

Out[116]:
```
0.08795397898453516
```

In [ ]:
```
model1.score(X_train1, y_train1)
```

Out[117]:
```
0.10540571792300835
```

When it comes to model interpretability, it is the same as we saw for OLS. There is hardly much difference.

Classification Techniques

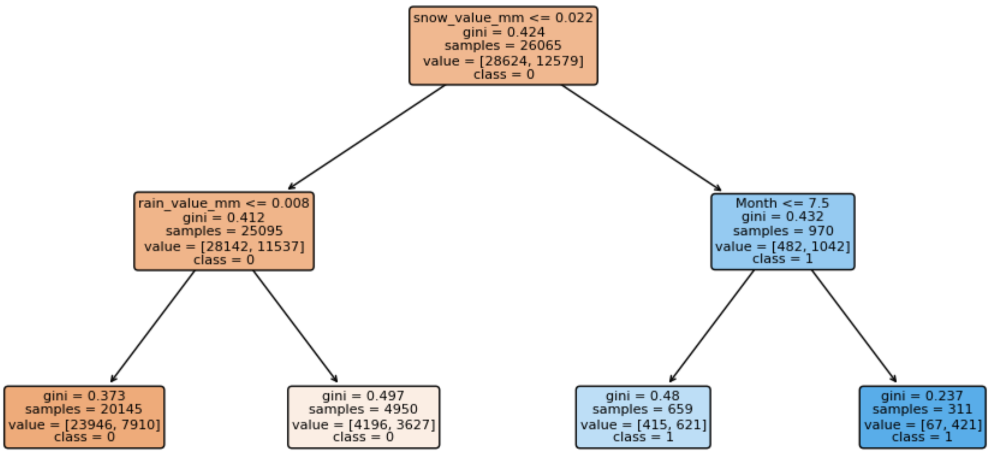
1. Random Forest Classifier

In [ ]:
```
y2= energydata['low_irradiation']
X2=energydata[['Day','Month','Year','snow_value_mm','total_daily_snow_mm',
X_train2, X_test2, y_train2, y_test2 = train_test_split(X2, y2,
                                                    test_size=0.2,
                                                    random_state=42)
```

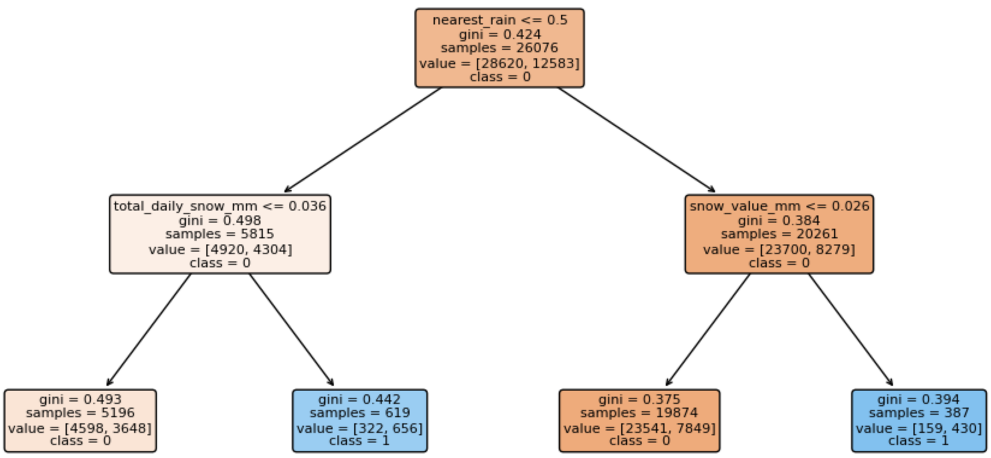
In [ ]:
```
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(n_estimators=3,
                             max_depth=2,
                             random_state=42)
rfc.fit(X_train2, y_train2)
y_pred2 = rfc.predict(X_test2)
```

In [ ]:
```
from sklearn import tree

features = X2.columns.values
classes = ['0', '1']

for estimator in rfc.estimators_:
    print(estimator)
    plt.figure(figsize=(12,6))
    tree.plot_tree(estimator,
                   feature_names=features,
                   class_names=classes,
                   fontsize=8,
                   filled=True,
                   rounded=True)
    plt.show()
```

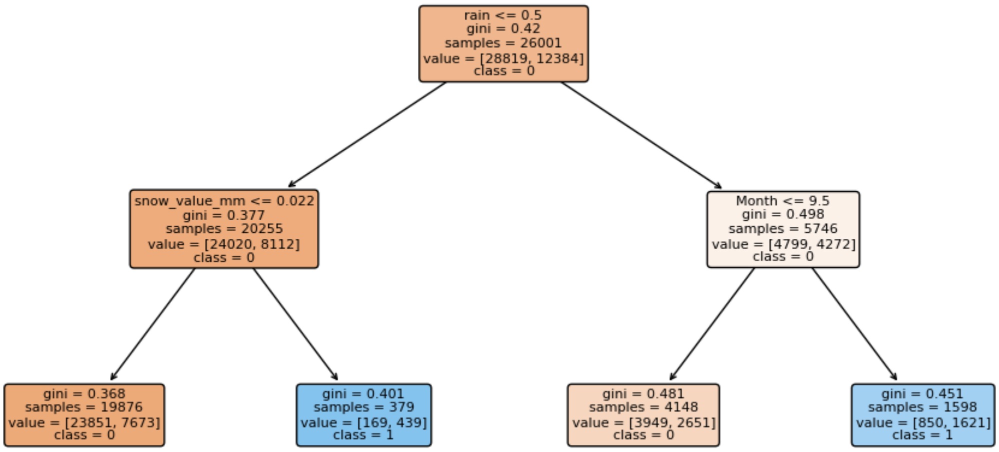
```
DecisionTreeClassifier(max_depth=2, max_features='sqrt',
                       random_state=1608637542)
```




```
DecisionTreeClassifier(max_depth=2, max_features='sqrt',
                       random_state=1273642419)
```

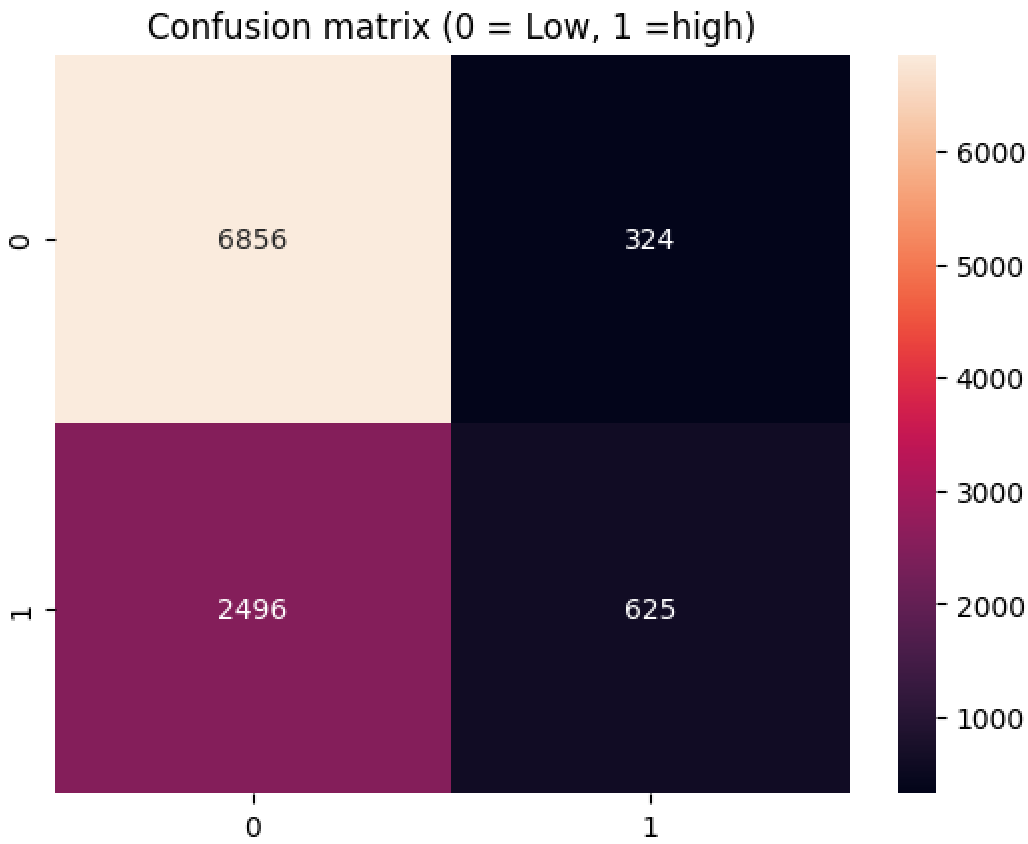



```
DecisionTreeClassifier(max_depth=2, max_features='sqrt',
                       random_state=1935803228)
```


rain <= 0.5
gini = 0.42
samples = 26001
value = [28819, 12384]
class = 0
snow_value_mm <= 0.022
gini = 0.377
samples = 20255
value = [24020, 8112]
class = 0
Month <= 9.5
gini = 0.498
samples = 5746
value = [4799, 4272]
class = 0
gini = 0.368
samples = 19876
value = [23851, 7673]
class = 0
gini = 0.401
samples = 379
value = [169, 439]
class = 1
gini = 0.481
samples = 4148
value = [3949, 2651]
class = 0
gini = 0.451
samples = 1598
value = [850, 1621]
class = 1

In [ ]:
```
from sklearn.metrics import classification_report, confusion_matrix

c = confusion_matrix(y_test2, y_pred2)
sb.heatmap(c, annot=True, fmt='d').set_title('Confusion matrix (0 = Low, 1

print(classification_report(y_test2,y_pred2))
```

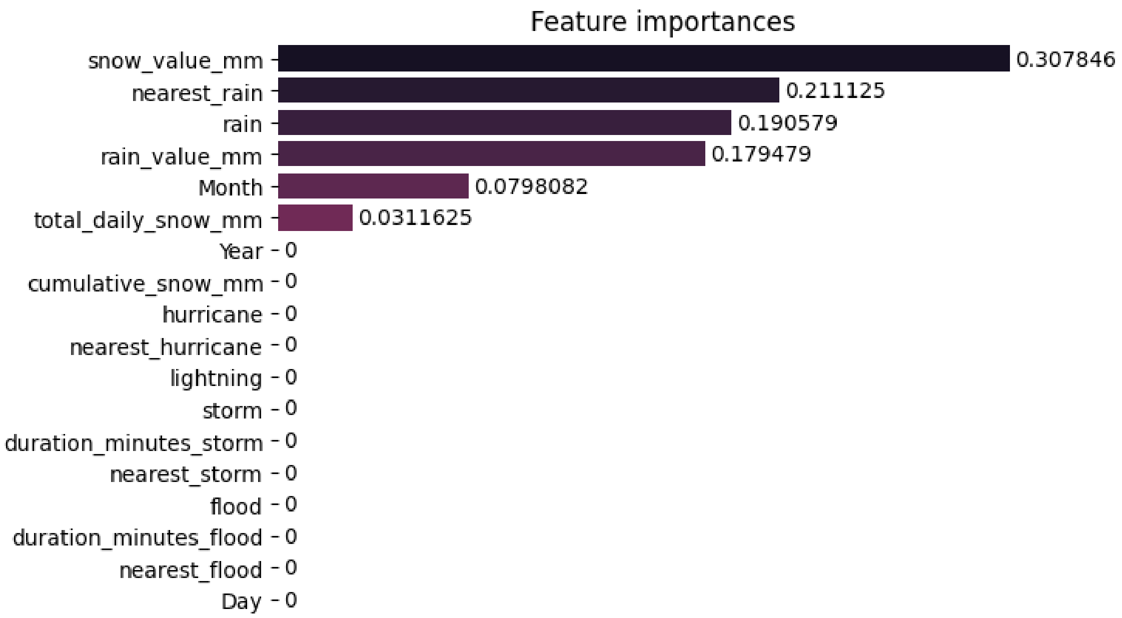
```
              precision    recall  f1-score   support

           0       0.73      0.95      0.83      7180
           1       0.66      0.20      0.31      3121

    accuracy                           0.73     10301
   macro avg       0.70      0.58      0.57     10301
weighted avg       0.71      0.73      0.67     10301
```



From the classification report, we see that precision for class 0 is moderately good and for class 1 it is okay. Recall for class 0 is excellent (0.95) as opposed to 0.20 for class 1 which is very poor. Finally, the f1 scores for both classes which summarizes precision and recall suggest that the model is doing quite good for class 0 and very poor for class 1. The accuracy achieved by the classifer is okay (73%).

Let us look at the importances of features now.

In [ ]:
```
features_df = pd.DataFrame({'features': rfc.feature_names_in_, 'importances

#Data is being sorted from highest to lowest
features_df_sorted = features_df.sort_values(by='importances', ascending=Fa

g = sb.barplot(data=features_df_sorted, x='importances', y ='features', pal
sb.despine(bottom = True, left = True)
g.set_title('Feature importances')
g.set(xlabel=None)
g.set(ylabel=None)
g.set(xticks=[])
for value in g.containers:
    g.bar_label(value, padding=2)
```



Feature importance is highest for snow_value_mm, nearest_rain, followed by rain, rain_value_mm and month.

2. Decision Tree Classifier

In [21]:
```
y3= energydata['low_irradiation']
X3=energydata[['Day','Month','Year','snow_value_mm','total_daily_snow_mm',
X_train3, X_test3, y_train3, y_test3 = train_test_split(X3, y3,
                                                        test_size=0.2,
                                                        random_state=42)
```

In [22]:
```
from sklearn.tree import DecisionTreeClassifier
classifier3 = DecisionTreeClassifier()
classifier3.fit(X_train3, y_train3)
```

Out[22]:
```
DecisionTreeClassifier()
```

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In [23]:
```
y_pred3 = classifier3.predict(X_test3)
```

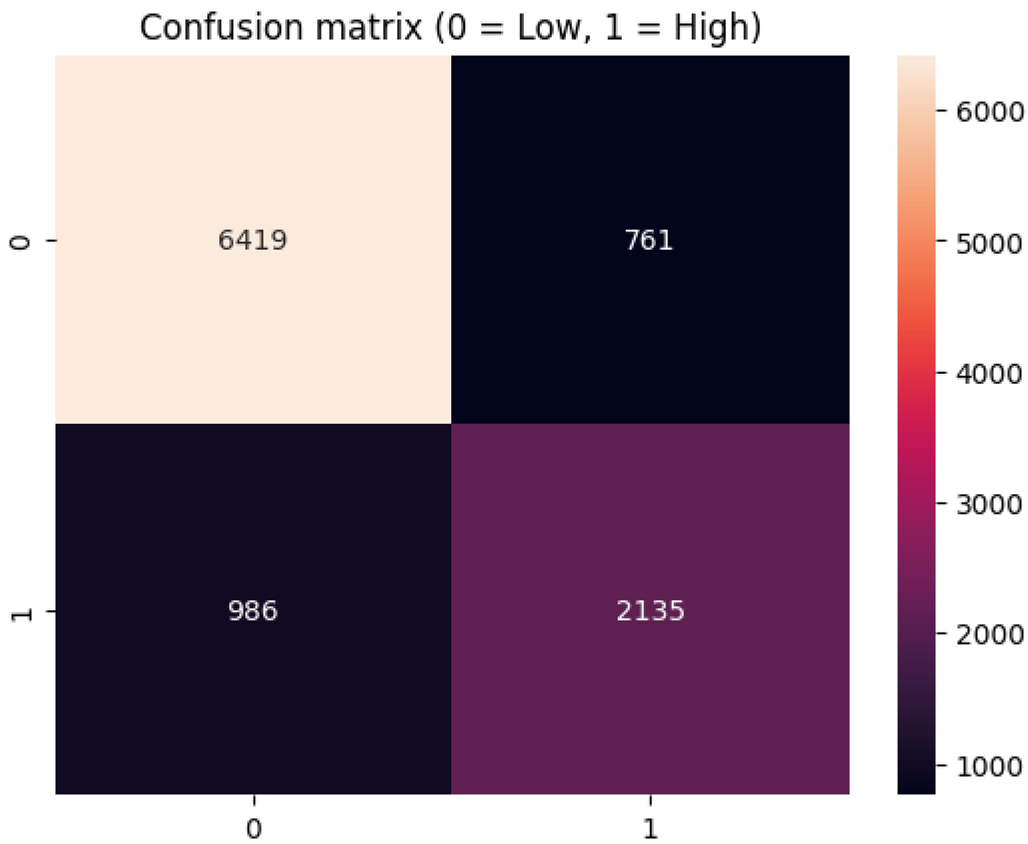
In [25]:
```
from sklearn.metrics import classification_report, confusion_matrix
c3=confusion_matrix(y_test3, y_pred3)
print(classification_report(y_test3, y_pred3))
sb.heatmap(c3, annot=True, fmt='d').set_title('Confusion matrix (0 = Low, 1
```

```
              precision    recall  f1-score   support

           0       0.87      0.89      0.88      7180
           1       0.74      0.68      0.71      3121

    accuracy                           0.83     10301
   macro avg       0.80      0.79      0.79     10301
weighted avg       0.83      0.83      0.83     10301
```

Out[25]:
```
Text(0.5, 1.0, 'Confusion matrix (0 = Low, 1 = High)')
```



From the classification report, we see that precision for class 0 is decent(0.87) and for class 1(0.74) it is okay. Recall for class 0 is decent (0.89) as opposed to 0.68 for class 1 which is moderately poor. Finally, the f1 scores for both classes have improved significantly and suggest that the model is doing quite good for class 0 and okay for class 1. The accuracy achieved by the classifer is decent this time (83%).

Conclusion

To conclude, the regression model had very poor accuracy and this analyses may not prove very useful. On the contrary, the classififcation models fared better especially the decision tree classifier which predicted the low_irradiation values.

In future, we could have a database that expands to other countries and continents like Europe where there is significant emphasis on sustainability and clean energy generation. Also, I believe that we could have another parameter that factors in weather phenomenons like El nino and la nina (https://www.climate.gov/enso (https://www.climate.gov/enso)) as these adversely affect the normal weather conditions. Fun fact : We have an el nino weather system currently in 2023 that could mean adverse weather conditions.

Prompt 1 : Suppose that some of the weather-related variables end up being in the regression/classification models you ultimately recommend. The true value of these quantities may not be observed until the day in question, in which case you have already observed the performance ratio and/or irradiation. For these weather-related variables to be used in practice for predicting the performance ratio or irradiation, we would need some day-ahead forecast of them. Any such forecast has uncertainty associated with it, e.g., we might only be able to predict tomorrow's wind speed as 10 m/s +/- 2 m/s. How would you incorporate this uncertainty surrounding the predictors in your predictions for the response?

I think a better way to handle these uncertainties would be to have some sort of probabilistic model that governs our analyis of this dataset. My reasoning is that if we have a probability instead of an absolute or point estimate, we will be able to account for those uncertainties which otherwise would give us an erroneous result. The central idea is that we need to have some tolerance and confidence in the predicted responses and that according to me can be captured in a probabilistic model.

Prompt 2 : Describe at least three limitations of your study. Examples include the unavailability of certain data and simplifying assumptions made. Explain how these might be addressed given additional time and resources.

1. I could have reduced the number of predictor variables using Principal Component Analysis and included only relevant ones that would make a difference to the output. Presently, the analyses include mostly all the variables and that could have inadvertently introduced errors.
2. For data preparation, I could have been specific when it came to imputing missing values. In this analysis, I just generalized numerical data imputation using mean values which could have been dealt with differently.
3. My study doesn't factor in the unbalanced nature of the dataset. The data appeared unbalanced for majority of the predictors as is evident from the histogram plots. I think that skewness could have been handled in a better manner. One way I can think is by extrapolating and expanding on the balanced part of the data using some transofrmation or by implementing Generative Adversarial Network (GAN) or by simply using oversampling techniques) Reference used - https://machinelearningmastery.com/data-sampling-methods-for-imbalanced-classification/ (https://machinelearningmastery.com/data-sampling-methods-for-imbalanced-classification/)