Nueva sección

```
import pickle
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_selection import RFE
from sklearn.linear_model import (
    LogisticRegression, LinearRegression, Ridge, Lasso, ElasticNet,
    BayesianRidge, PassiveAggressiveRegressor
)
from sklearn.neighbors import KNeighborsClassifier, KNeighborsRegressor
from sklearn.svm import SVC, SVR
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import (
    RandomForestClassifier, AdaBoostClassifier, ExtraTreesClassifier,
    RandomForestRegressor, GradientBoostingRegressor
)
from sklearn.metrics import (
    roc_auc_score, precision_score, recall_score, f1_score, r2_score, mean_squared_error,
    accuracy_score, log_loss, confusion_matrix, classification_report,
    mean_absolute_error, explained_variance_score
)
import xgboost as xgb
from tqdm.auto import tqdm
import seaborn as sns

from lightgbm import LGBMClassifier
from sklearn.neural_network import MLPRegressor
from sklearn.neighbors import LocalOutlierFactor
from sklearn.decomposition import PCA
from sklearn.covariance import EllipticEnvelope
from sklearn.cluster import KMeans
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler, label_binarize, LabelEncoder
plt.rcParams['figure.figsize']=[10,5]
from sklearn.utils import shuffle
from imblearn.over_sampling import SMOTE
import plotly.graph_objects as go
from sklearn.feature_selection import RFE
import plotly.express as px
from sklearn.model_selection import train_test_split, GridSearchCV
```

```
from google.colab import drive
drive.mount('/content/drive')

df = pd.read_csv("/content/drive/MyDrive/Steel_industry_data.csv");

# Load columns

df.head()
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remoun
```

	date	Usage_kWh	Lagging_Current_Reactive.Power_kVarh	Leading_Current_Reactive_Power_kVarh	CO2(tCO2)	Lagging_Cu
0	01/01/2018 00:15	3.17	2.95	0.0	0.0	
1	01/01/2018 00:30	4.00	4.46	0.0	0.0	
2	01/01/2018 00:45	3.24	3.28	0.0	0.0	
3	01/01/2018 01:00	3.31	3.56	0.0	0.0	
4	01/01/2018 01:15	3.82	4.50	0.0	0.0	

```
# Shape dataset
# We check here ho many rows has the dataset

df.shape
```

```
(35040, 11)
```

```
# Colum names array

df.columns
```

```
Index(['date', 'Usage_kWh', 'Lagging_Current_Reactive.Power_kVarh',
       'Leading_Current_Reactive_Power_kVarh', 'CO2(tCO2)',
       'Lagging_Current_Power_Factor', 'Leading_Current_Power_Factor', 'NSM',
       'WeekStatus', 'Day_of_week', 'Load_Type'],
      dtype='object')
```

```
# Check data types

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35040 entries, 0 to 35039
Data columns (total 11 columns):
 #   Column                                Non-Null Count  Dtype  
---  ------                                --------------  -----  
 0   date                                  35040 non-null  object 
 1   Usage_kWh                             35040 non-null  float64
 2   Lagging_Current_Reactive.Power_kVarh  35040 non-null  float64
 3   Leading_Current_Reactive_Power_kVarh  35040 non-null  float64
 4   CO2(tCO2)                             35040 non-null  float64
 5   Lagging_Current_Power_Factor          35040 non-null  float64
 6   Leading_Current_Power_Factor          35040 non-null  float64
 7   NSM                                   35040 non-null  int64  
 8   WeekStatus                            35040 non-null  object 
 9   Day_of_week                           35040 non-null  object 
 10  Load_Type                             35040 non-null  object 
dtypes: float64(6), int64(1), object(4)
memory usage: 2.9+ MB
```

```
# Check null values

df.isnull().sum()
```

```
date                                    0
Usage_kWh                               0
Lagging_Current_Reactive.Power_kVarh    0
Leading_Current_Reactive_Power_kVarh    0
CO2(tCO2)                               0
Lagging_Current_Power_Factor            0
Leading_Current_Power_Factor            0
NSM                                     0
WeekStatus                              0
Day_of_week                             0
Load_Type                               0
dtype: int64
```

```
# Check number of unique values

df.nunique()
```

```
date                                    35040
Usage_kWh                                3343
Lagging_Current_Reactive.Power_kVarh     1954
Leading_Current_Reactive_Power_kVarh      768
CO2(tCO2)                                   8
Lagging_Current_Power_Factor             5079
Leading_Current_Power_Factor             3366
NSM                                        96
WeekStatus                                  2
Day_of_week                                 7
Load_Type                                   3
dtype: int64
```

```
# Data Transformation:
# Encode Categorical Columns
categ = df.select_dtypes(include = "object").columns

columns_to_convert = ['NSM']
df[columns_to_convert] = df[columns_to_convert].astype(float)

le = LabelEncoder()
df[categ] = df[categ].apply(le.fit_transform)
#count the value for load type after LabelEncoder
df["Load_Type"].value_counts()
```

```
Load_Type
0    18072
2     9696
1     7272
Name: count, dtype: int64
```

```
df.head()
```

	date	Usage_kWh	Lagging_Current_Reactive.Power_kVarh	Leading_Current_Reactive_Power_kVarh	CO2(tCO2)	Lagging_Curren
0	1	3.17	2.95	0.0	0.0	
1	2	4.00	4.46	0.0	0.0	
2	3	3.24	3.28	0.0	0.0	
3	4	3.31	3.56	0.0	0.0	
4	5	3.82	4.50	0.0	0.0	

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35040 entries, 0 to 35039
Data columns (total 11 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   date                                  35040 non-null  int64
 1   Usage_kWh                             35040 non-null  float64
 2   Lagging_Current_Reactive.Power_kVarh  35040 non-null  float64
 3   Leading_Current_Reactive_Power_kVarh  35040 non-null  float64
 4   CO2(tCO2)                             35040 non-null  float64
 5   Lagging_Current_Power_Factor          35040 non-null  float64
 6   Leading_Current_Power_Factor          35040 non-null  float64
 7   NSM                                   35040 non-null  float64
 8   WeekStatus                            35040 non-null  int64
 9   Day_of_week                           35040 non-null  int64
 10  Load_Type                             35040 non-null  int64
dtypes: float64(7), int64(4)
memory usage: 2.9 MB
```

```
df = df.drop('date', axis=1)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35040 entries, 0 to 35039
Data columns (total 10 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   Usage_kWh                             35040 non-null  float64
 1   Lagging_Current_Reactive.Power_kVarh  35040 non-null  float64
 2   Leading_Current_Reactive_Power_kVarh  35040 non-null  float64
 3   CO2(tCO2)                             35040 non-null  float64
 4   Lagging_Current_Power_Factor          35040 non-null  float64
 5   Leading_Current_Power_Factor          35040 non-null  float64
 6   NSM                                   35040 non-null  float64
 7   WeekStatus                            35040 non-null  int64
 8   Day_of_week                           35040 non-null  int64
 9   Load_Type                             35040 non-null  int64
dtypes: float64(7), int64(3)
memory usage: 2.7 MB
```

```
# Data Augmentation
# Apply random noise
noisy_df = df.apply(lambda x: x + np.random.normal(0, 0.01, len(x)) if x.dtype == 'float' else x)

# Duplicate and shuffle
duplicated_df = pd.concat([df] * 2, ignore_index=True)
shuffled_df = shuffle(duplicated_df)

# Apply SMOTE
X = df.drop('Load_Type', axis=1)
y = df['Load_Type']

smote = SMOTE()
X_resampled, y_resampled = smote.fit_resample(X, y)

X_resampled['Load_Type'] = y_resampled
df_aug = X_resampled
df_aug.head()
```

	Usage_kWh	Lagging_Current_Reactive.Power_kVarh	Leading_Current_Reactive_I
0	3.17	2.95	
1	4.00	4.46	
2	3.24	3.28	
3	3.31	3.56	
4	3.82	4.50	

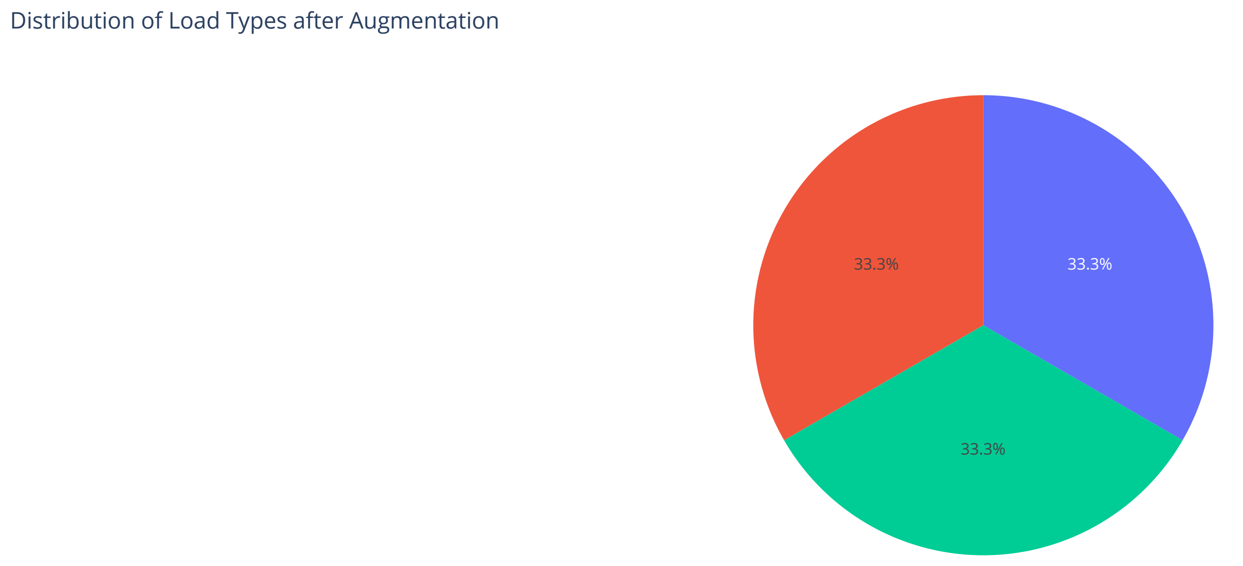
```
df_aug.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54216 entries, 0 to 54215
Data columns (total 10 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   Usage_kWh                             54216 non-null  float64
 1   Lagging_Current_Reactive.Power_kVarh  54216 non-null  float64
 2   Leading_Current_Reactive_Power_kVarh  54216 non-null  float64
 3   CO2(tCO2)                             54216 non-null  float64
 4   Lagging_Current_Power_Factor          54216 non-null  float64
 5   Leading_Current_Power_Factor          54216 non-null  float64
 6   NSM                                   54216 non-null  float64
 7   WeekStatus                            54216 non-null  int64
 8   Day_of_week                           54216 non-null  int64
 9   Load_Type                             54216 non-null  int64
dtypes: float64(7), int64(3)
memory usage: 4.1 MB
```

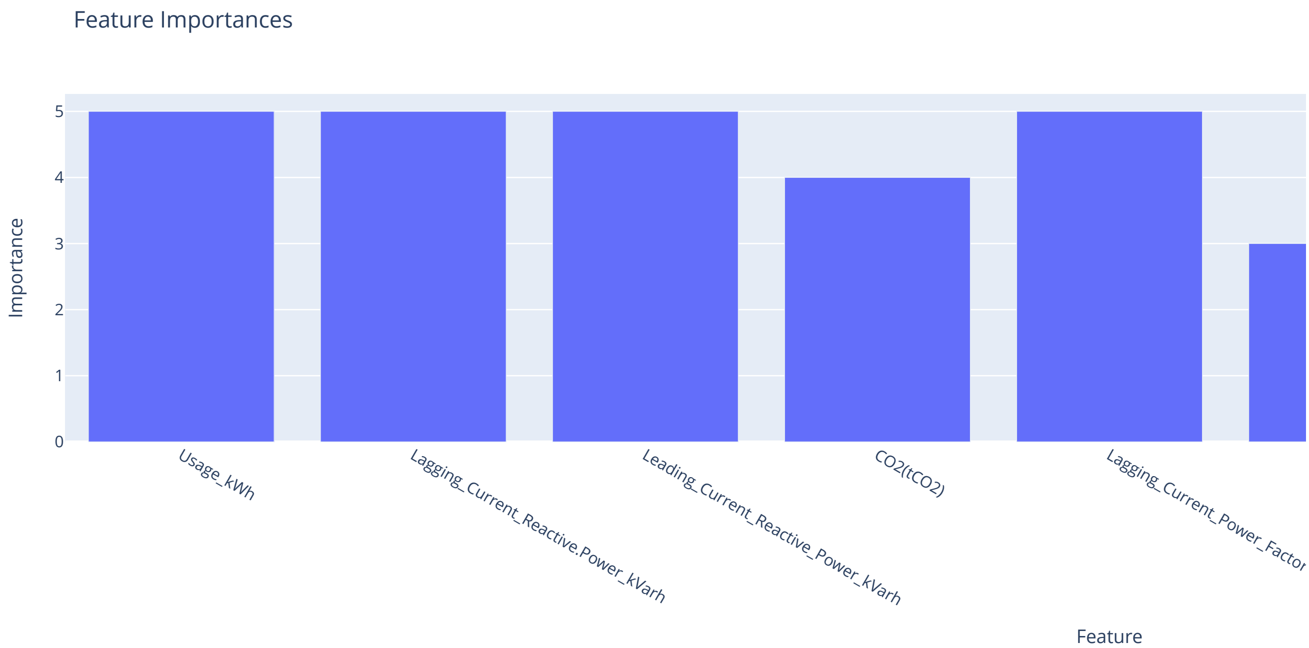
```
#count the value for load type after data augmentstion
df_aug["Load_Type"].value_counts()
```

```
Load_Type
0    18072
2    18072
1    18072
Name: count, dtype: int64
```

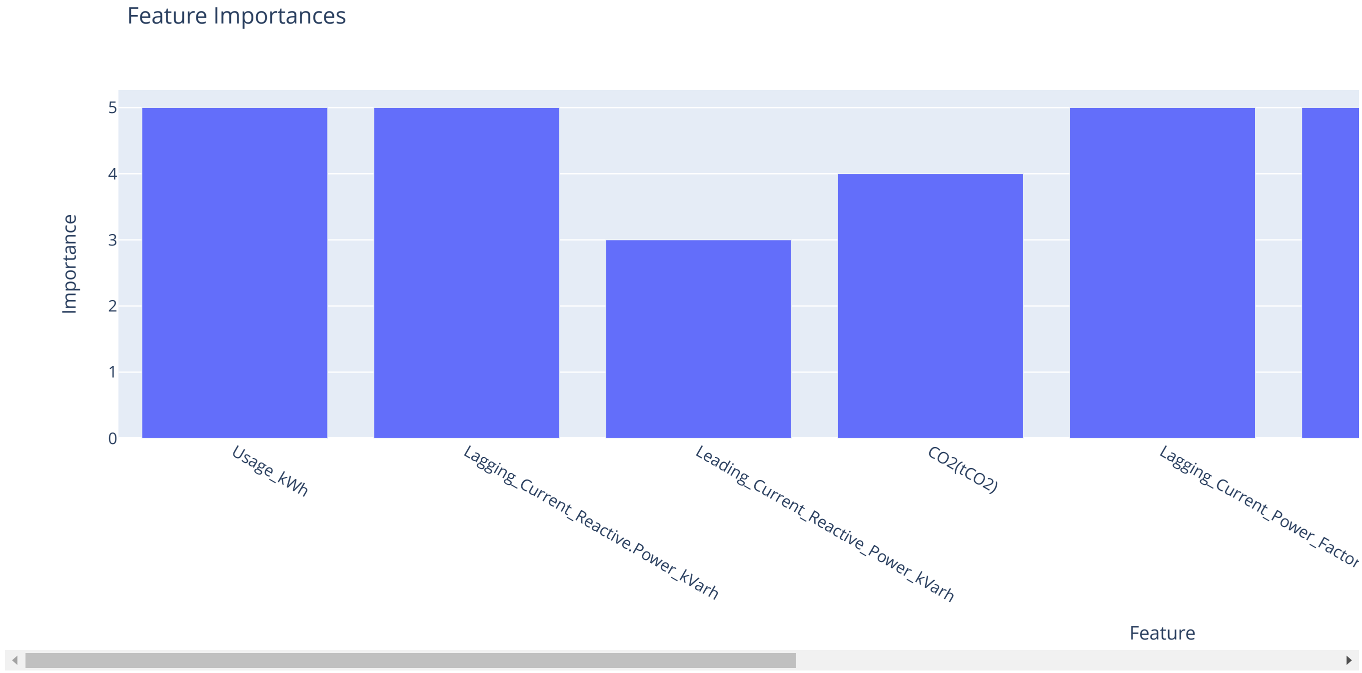
```
# Count the occurrences of each load type
load_type_counts = df_aug['Load_Type'].value_counts()

labals_lis = ['Light Load',
              'Medium Load',
              'Maximum Load' ]

# Create the pie chart
fig = go.Figure(data=[go.Pie(labels=labals_lis, values=load_type_counts.values)])
fig.update_layout(title='Distribution of Load Types after Augmentation')
fig.show()
```




```
def feature_selection_using_RF(x,y):
    model = RandomForestClassifier()
    rfe = RFE(model, n_features_to_select=5)  # Choose the number of features to select
    rfe.fit(x, y)

    selected_features = x.columns[rfe.support_]
    importances = np.max(rfe.ranking_) + 1 - rfe.ranking_
    fig = px.bar(x=x.columns, y=importances, labels={'x': 'Feature', 'y': 'Importance'},
                 title='Feature Importances')
    fig.show()
    x = x[selected_features]
    return x,y
x = df.drop(['Load_Type'], axis=1)
y = df.Load_Type
xg = df_aug.drop(['Load_Type'], axis=1)
yg = df_aug.Load_Type
x , y = feature_selection_using_RF(x,y)
```




```
xg , yg = feature_selection_using_RF(xg,yg)
```




```
# Split the dataset and prepare some lists to store the models
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25, random_state = 42)
xg_train, xg_test, yg_train, yg_test = train_test_split(xg, yg, test_size=0.25, random_state = 42)


#Loop for the training model
names = [
    "Logistic Regression",
    "KNN",
    "Decision Tree",
    "Naive Bayes",
    "Random Forest",
    "Random Forest with Extra Trees",
    "AdaBoost",
    "XGBoost"
]

clf = [
    LogisticRegression(),
    KNeighborsClassifier(3),
    DecisionTreeClassifier(max_depth=5),
    GaussianNB(),
    RandomForestClassifier(n_estimators=200, max_leaf_nodes=16),
    ExtraTreesClassifier(),
    AdaBoostClassifier(DecisionTreeClassifier(max_depth=3)),
    xgb.XGBClassifier()
]


def train_clf(x_train, y_train,x_test, y_test):
    scores = []
    for model in tqdm(clf):
        model.fit(x_train, y_train)
        score = model.score(x_test, y_test)
        scores.append(score)
#         print(model)
#         print(score)
    return pd.DataFrame(zip(names,scores), columns=['Classifier', 'Accuracy'])


#List the classifier and their accuracy
scores_df = train_clf(x_train, y_train,x_test, y_test)
scores_df = scores_df.sort_values(by=['Accuracy'], ascending=[False])
print(scores_df)

# Plot the accuracies using Plotly Express
fig = px.bar(scores_df, x='Classifier', y='Accuracy', labels={'Classifier': 'Classifier', 'Accuracy': 'Accuracy'},
             title='Classifier Accuracies')
fig.update_layout(xaxis_title='Classifier', yaxis_title='Accuracy')
fig.show()
```

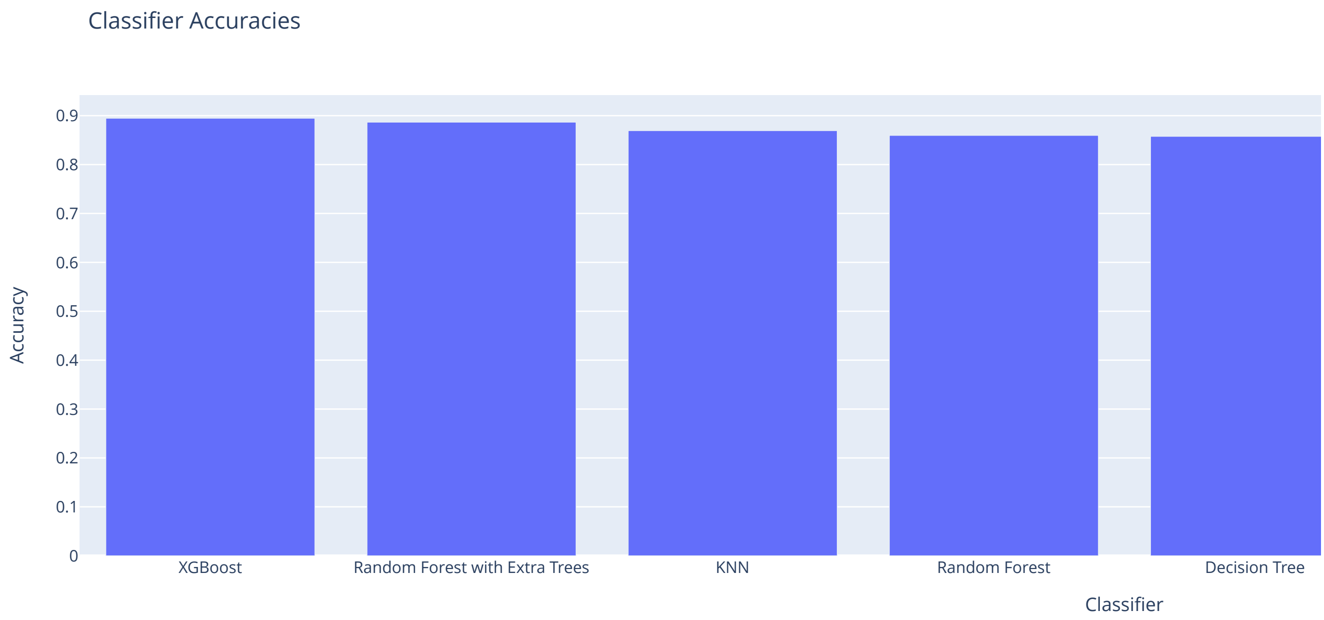
100% 8/8 [00:10<00:00, 1.34s/it]

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

                    Classifier  Accuracy
7                      XGBoost  0.894635
5  Random Forest with Extra Trees  0.886644
1                          KNN  0.869292
4                Random Forest  0.859589
2                Decision Tree  0.857648
6                     AdaBoost  0.812557
3                  Naive Bayes  0.704338
0          Logistic Regression  0.703425
```

```
#List the classifier and their accuracy
scores_df_aug = train_clf(xg_train, yg_train,xg_test, yg_test)
scores_df_aug = scores_df_aug.sort_values(by=['Accuracy'], ascending=[False])
print(scores_df)

# Plot the accuracies using Plotly Express
fig = px.bar(scores_df_aug, x='Classifier', y='Accuracy', labels={'Classifier': 'Classifier', 'Accuracy': 'Accuracy'},
             title='Classifier Accuracies')
fig.update_layout(xaxis_title='Classifier', yaxis_title='Accuracy')
fig.show()
```

```
100%                                    8/8 [00:17<00:00,  2.49s/it]
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

                     Classifier  Accuracy
7                       XGBoost  0.894635
5  Random Forest with Extra Trees  0.886644
1                           KNN  0.869292
4                 Random Forest  0.859589
2                 Decision Tree  0.857648
6                      AdaBoost  0.812557
3                   Naive Bayes  0.704338
0           Logistic Regression  0.703425
```

```
# Plot the accuracies using Plotly Express
fig = px.bar(scores_df, x='Classifier', y='Accuracy', labels={'Classifier': 'Classifier', 'Accuracy': 'Accuracy'},
             title='Classifier Accuracies')
fig.update_layout(xaxis_title='Classifier', yaxis_title='Accuracy')
fig.show()
```




```
#Naive grid search implementation
parameters = {'max_depth': range (2, 10, 1),
    'n_estimators': range(60, 220, 40),
    'learning_rate': [0.1, 0.01, 0.05]}
CBC = xgb.XGBClassifier()
Grid_CBC = GridSearchCV(estimator=CBC, param_grid = parameters, cv = 2, n_jobs=-1)
Grid_CBC.fit(xg_train, yg_train)

print("Results from Grid Search" )
print("\n The best estimator across ALL searched params:\n",Grid_CBC.best_estimator_)
print("\n The best score across ALL searched params:\n",Grid_CBC.best_score_)
print("\n The best parameters across ALL searched params:\n",Grid_CBC.best_params_)
```

```
Results from Grid Search

 The best estimator across ALL searched params:
 XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=9, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=180, n_jobs=None,
              num_parallel_tree=None, objective='multi:softprob', ...)

 The best score across ALL searched params:
 0.8909792927057203

 The best parameters across ALL searched params:
 {'learning_rate': 0.1, 'max_depth': 9, 'n_estimators': 180}
```

```
#This is the classification model with the best parameters
Grid_CBC
```

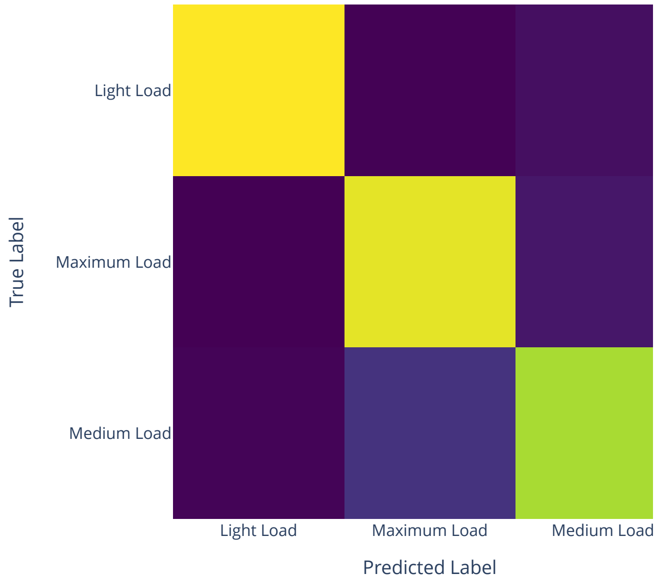
```
▸ GridSearchCV
▸ estimator: XGBClassifier
    ▸ XGBClassifier
```

```
# Make predictions on the test set
yg_pred = Grid_CBC.predict(xg_test)
```

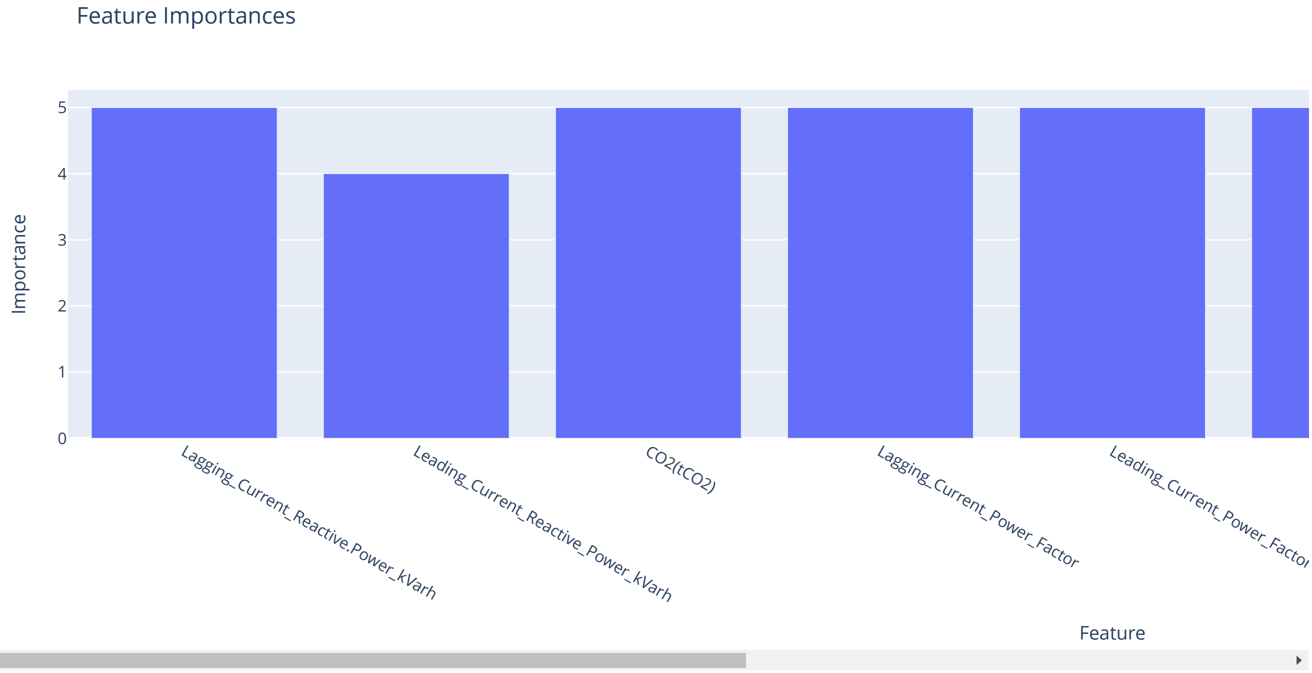
```
# Calculate evaluation metrics
def cls_report(y_test, y_pred):
    y_test_binarized = label_binarize(y_test, classes=[0, 1, 2])
    n_classes = y_test_binarized.shape[1]
    y_pred_reshaped = y_pred.reshape(-1, 1)
    class_report = classification_report(y_test, y_pred)
    conf_matrix = confusion_matrix(y_test, y_pred)
    roc_auc = roc_auc_score(y_test_binarized, y_pred_reshaped)
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    return class_report, conf_matrix, roc_auc, mse, r2


class_report, conf_matrix, roc_auc, mse, r2 = cls_report(yg_test, yg_pred)



# Print the results
print(f"AUC-ROC: {roc_auc:.4f}")
print('Mean Squared Error:', mse)
print('R-squared:', r2)
print("\nClassification Report:")
print(class_report)
print("Confusion Matrix:")
print(conf_matrix)

# Create a DataFrame for the confusion matrix
classes = ['Light Load','Maximum Load' ,  ' Medium Load']
df_cm = pd.DataFrame(conf_matrix, index=classes, columns=classes)

# Plot the confusion matrix heatmap using Plotly Express
fig = px.imshow(df_cm,
                labels=dict(x="Predicted Label", y="True Label", color="Count"),
                x=classes,
                y=classes,
                color_continuous_scale='Viridis')

# Customize the layout
fig.update_layout(title='Confusion Matrix',
                  xaxis_title='Predicted Label',
                  yaxis_title='True Label')

# Show the plot
fig.show()
```

```
AUC-ROC: 0.0413
Mean Squared Error: 0.15559982293050023
R-squared: 0.7673130206082096

Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.95      0.96      4565
           1       0.85      0.93      0.89      4490
           2       0.88      0.84      0.86      4499

    accuracy                           0.90     13554
   macro avg       0.90      0.90      0.90     13554
weighted avg       0.90      0.90      0.90     13554

Confusion Matrix:
[[4323   45  197]
 [  29 4158  303]
 [  68  672 3759]]
```

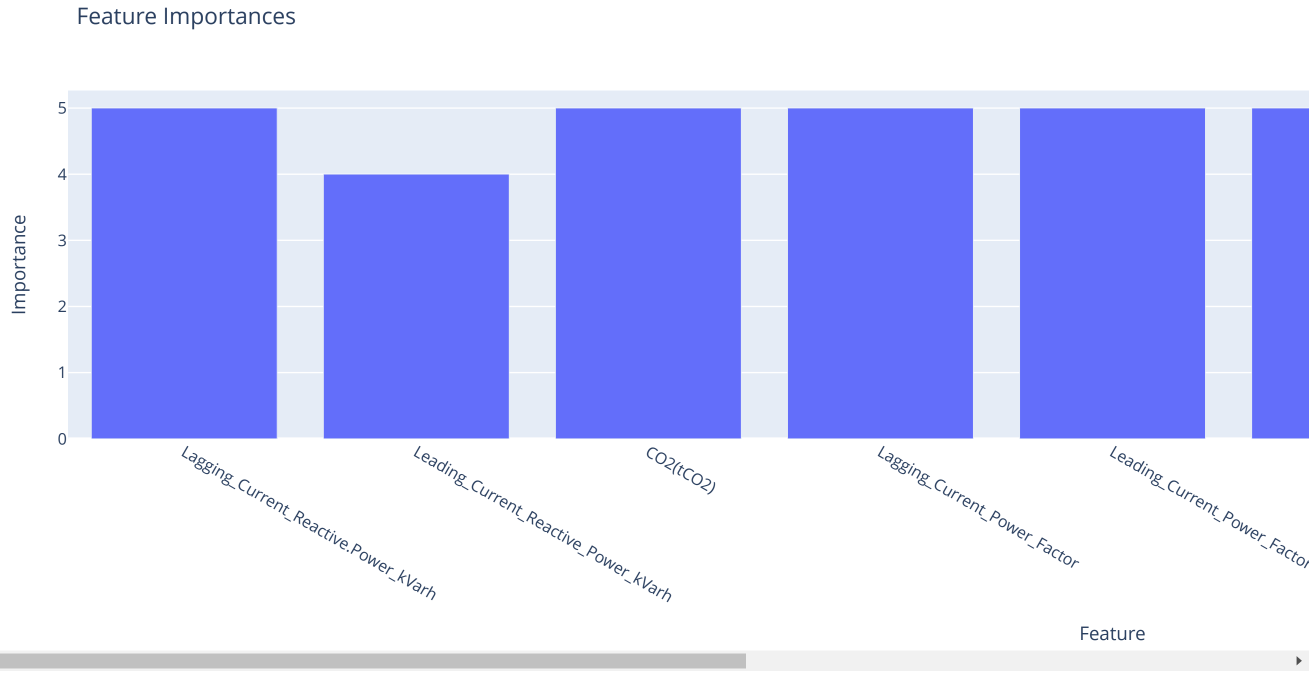
Confusion Matrix




```
# Now we try regression models

def feature_selection_using_RFR(x,y):
    model = RandomForestRegressor()
    rfe = RFE(model, n_features_to_select=5)  # Choose the number of features to select
    rfe.fit(x, y)

    selected_features = x.columns[rfe.support_]
    importances = np.max(rfe.ranking_) + 1 - rfe.ranking_
    fig = px.bar(x=x.columns, y=importances, labels={'x': 'Feature', 'y': 'Importance'},
                 title='Feature Importances')
    fig.show()
    x = x[selected_features]
    return x,y
# Split the dataset and prepare some lists to store the models
x = df.drop(['Usage_kWh'], axis=1)
y = df.Usage_kWh
# Split the dataset and prepare some lists to store the models
xg = df_aug.drop(['Usage_kWh'], axis=1)
yg = df_aug.Usage_kWh
x , y = feature_selection_using_RFR(x,y)
```




```
xg , yg = feature_selection_using_RFR(xg,yg)
```




```
# Split the dataset and prepare some lists to store the models
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25, random_state = 42)
xg_train, xg_test, yg_train, yg_test = train_test_split(xg, yg, test_size=0.25, random_state = 42)
```

```
#Loop for the training model
names = [
    "Linear Regression",
    "Ridge Regression",
    "Decision Tree Regression",
    "Random Forest Regression",
    "Gradient Boosting Regression",
    "KNN Regression",
    "Bayesian Ridge Regression",
    "XGBoost Regression"
]

reg = [
    LinearRegression(),
    Ridge(alpha=0.5),
    DecisionTreeRegressor(max_depth=5),
    RandomForestRegressor(n_estimators=5,max_depth=5),
    GradientBoostingRegressor(),
    KNeighborsRegressor(n_neighbors=35,leaf_size=50),
    BayesianRidge(),
    xgb.XGBRegressor()
]
def train_reg(x_train, y_train,x_test, y_test):
    scores = []
    for model in tqdm(reg):
        model.fit(x_train, y_train)
        score = model.score(x_test, y_test)
        scores.append(score)
#         print(model)
#         print(score)
    return pd.DataFrame(zip(names,scores), columns=['Regressor', 'Accuracy'])
#List the Regressor and their accuracy
scores_df = train_reg(x_train, y_train,x_test, y_test)
scores_df = scores_df.sort_values(by=['Accuracy'], ascending=[False])
print(scores_df)

# Plot the accuracies using Plotly Express
fig = px.bar(scores_df, x='Regressor', y='Accuracy', labels={'Regressor': 'Regressor', 'Accuracy': 'Accuracy'},
             title='Regression Model Accuracies')
fig.update_layout(xaxis_title='Regressor', yaxis_title='Accuracy')
fig.show()
```

100% 8/8 [00:03<00:00, 2.81it/s]

```
                      Regressor  Accuracy
7            XGBoost Regression  0.998912
4  Gradient Boosting Regression  0.992685
3      Random Forest Regression  0.989727
2      Decision Tree Regression  0.988738
0             Linear Regression  0.984465
6     Bayesian Ridge Regression  0.984465
1              Ridge Regression  0.969127
5                KNN Regression  0.935652
```

```
#List the Regressor and their accuracy
scores_df_aug = train_reg(xg_train, yg_train,xg_test, yg_test)
scores_df_aug = scores_df_aug.sort_values(by=['Accuracy'], ascending=[False])
print(scores_df_aug)

# Plot the accuracies using Plotly Express
fig = px.bar(scores_df_aug, x='Regressor', y='Accuracy', labels={'Regressor': 'Regressor', 'Accuracy': 'Accuracy'},
             title='Regression Model Accuracies')
fig.update_layout(xaxis_title='Regressor', yaxis_title='Accuracy')
fig.show()
```

```
100%                                   8/8  [00:08<00:00,    1.13s/it]
                     Regressor  Accuracy
7           XGBoost Regression  0.998873
4  Gradient Boosting Regression  0.992158
3      Random Forest Regression  0.986695
2      Decision Tree Regression  0.986168
0            Linear Regression  0.981000
6     Bayesian Ridge Regression  0.981000
1             Ridge Regression  0.973951
5               KNN Regression  0.965106
```

```
#Naive grid search implementation
parameters = {'max_depth': range (2, 10, 1),
    'n_estimators': range(60, 220, 40),
    'learning_rate': [0.1, 0.01, 0.05]}
CBC = xgb.XGBRegressor()
Grid_CBC = GridSearchCV(estimator=CBC, param_grid = parameters, cv = 2, n_jobs=-1)
Grid_CBC.fit(xg_train, yg_train)

print("Results from Grid Search" )
print("\n The best estimator across ALL searched params:\n",Grid_CBC.best_estimator_)
print("\n The best score across ALL searched params:\n",Grid_CBC.best_score_)
print("\n The best parameters across ALL searched params:\n",Grid_CBC.best_params_)
```

```
Results from Grid Search

 The best estimator across ALL searched params:
 XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.1, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=8, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
```