







COMBINED-CYCLE POWER PLANT

DATA SCIENCE PROJECT



PROJECT DETAILS

TEAM MEMBERS

| | | | | | |
|---|---|---|---|---|---|
|  |  |  |  |  |  |
| VAISHNAVI N | MANPREET BANJA | VAIBHAV HINDIA | ANKIT YADAV | MEGHA S K | SUSHRUTHA UK |

| | |
|-----------------------------------|---------|
| Introduction & Business objective | 01 - 02 |
| Project Architecture | 03 |
| Data Set Details | 04 |
| Exploratory Data Analysis (EDA) | 05 |
| Visualizations | 06 |
| Overview report of EDA | 07 |
| Model Building | 08 |
| Final Best Model chosen | 09 |



Thesis Presentation Outline

INTRODUCTION

- A combined-cycle power plant comprises of gas turbines, steam turbines, and heat recovery steam generators.
- In this type of plant, the electricity is generated by gas and steam turbines combined in one cycle. Then, it is transferred from one turbine to another.
- A Combined cycle power plant is a highly efficient power generation unit. They are clean and highly efficient.
- The process of combined cycle power generation recovers the temperature from the exhaust gas and utilizes that heat in power generation.

BUSINESS MODEL OBJECTIVE

The objective of the project is that we have to model the energy generated as a function of exhaust vacuum and ambient variables and use that model to improve the plant's performance.
This is a project where the variable to be predicted is energy production.

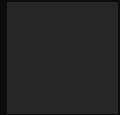
PROJECT ARCHITECTURE



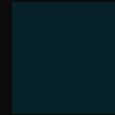
Data Set Details

Areas that you may wish to cover

The data file contains 9568 observations with five variables collected from a combined cycle power plant over six years when the power plant was set to work with a full load. The variables are the following:



Temperature (in degrees Celsius).



Ambient pressure (in millibar).



Exhaust vacuum (in cm Hg).



Relative humidity (in percentage).



Energy Production (in MW) net hourly
electrical energy output.



Exploratory Data Analysis (EDA)

```
In [2]: #Loading the Dataset  
df = pd.read_csv('energy_production.csv')  
df.head()
```

```
Out[2]:
```

| | temperature | exhaust_vacuum | amb_pressure | r_humidity | energy_production |
|---|-------------|----------------|--------------|------------|-------------------|
| 0 | 9.59 | 38.56 | 1017.01 | 60.10 | 481.30 |
| 1 | 12.04 | 42.34 | 1019.72 | 94.67 | 465.36 |
| 2 | 13.87 | 45.08 | 1024.42 | 81.69 | 465.48 |
| 3 | 13.72 | 54.30 | 1017.89 | 79.08 | 467.05 |
| 4 | 15.14 | 49.64 | 1023.78 | 75.00 | 463.58 |



```
In [3]: #Checking for NULL values
df.isnull().sum()
```

```
Out[3]: temperature      0
exhaust_vacuum          0
amb_pressure            0
r_humidity              0
energy_production       0
dtype: int64
```

INFERENCE :There are no NULL Values in the dataset

```
In [4]: #Shape of Dataset
df.shape
```

```
Out[4]: (9568, 5)
```

```
In [5]: #Data types of variables
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9568 entries, 0 to 9567
Data columns (total 5 columns):
#   Column              Non-Null Count  Dtype
---  ---
0   temperature         9568 non-null   float64
1   exhaust_vacuum      9568 non-null   float64
2   amb_pressure        9568 non-null   float64
3   r_humidity          9568 non-null   float64
4   energy_production   9568 non-null   float64
dtypes: float64(5)
memory usage: 373.9 KB
```

INFERENCE: There are no NULL Values in the dataset.



CHECKING FOR DUPLICATE VALUES

```
df=df.drop_duplicates()  
df
```

| | temperature | exhaust_vacuum | amb_pressure | r_humidity | energy_production |
|------|-------------|----------------|--------------|------------|-------------------|
| 0 | 9.59 | 38.56 | 1017.01 | 60.10 | 481.30 |
| 1 | 12.04 | 42.34 | 1019.72 | 94.67 | 465.36 |
| 2 | 13.87 | 45.08 | 1024.42 | 81.89 | 485.48 |
| 3 | 13.72 | 54.30 | 1017.89 | 79.08 | 467.05 |
| 4 | 15.14 | 49.64 | 1023.78 | 75.00 | 463.58 |
| ... | ... | ... | ... | ... | ... |
| 9563 | 17.10 | 49.69 | 1005.53 | 81.82 | 457.32 |
| 9564 | 24.73 | 65.34 | 1015.42 | 52.80 | 446.92 |
| 9565 | 30.44 | 56.24 | 1005.19 | 56.24 | 429.34 |
| 9566 | 23.00 | 66.05 | 1020.61 | 80.29 | 421.57 |
| 9567 | 17.75 | 49.25 | 1020.86 | 63.67 | 454.41 |

9527 rows x 5 columns

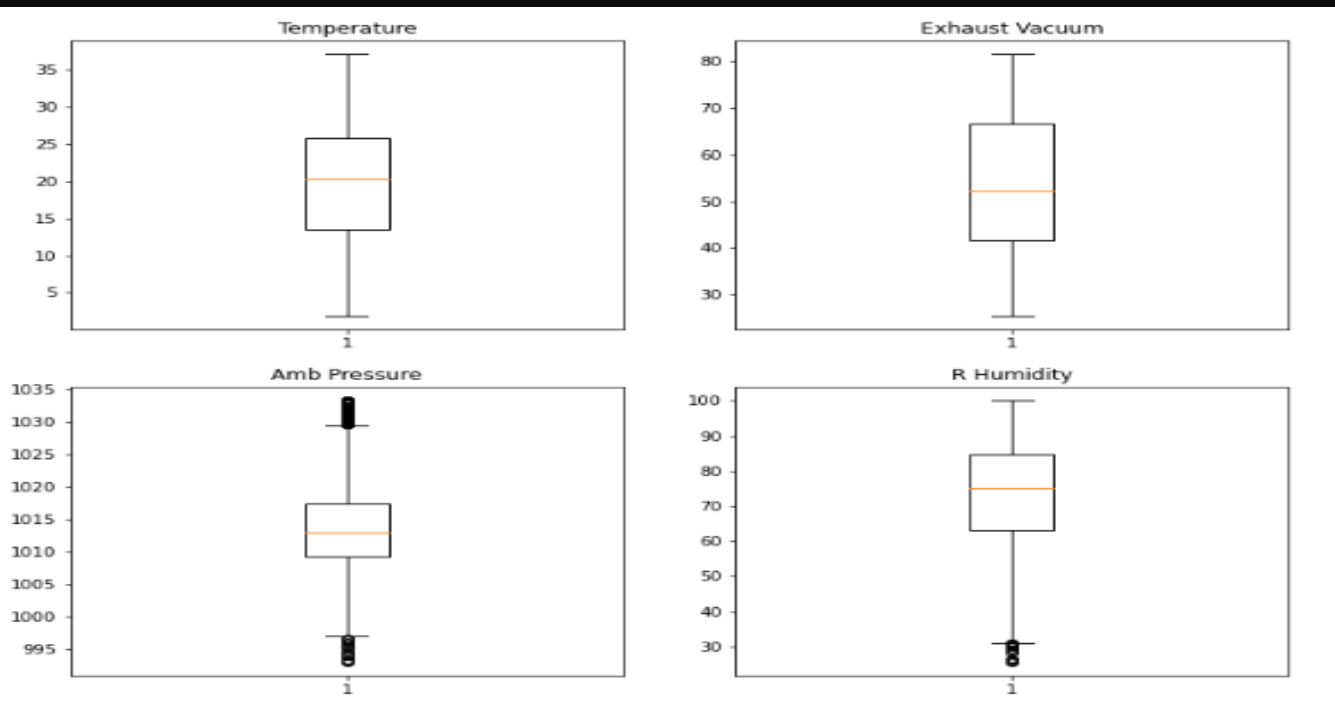
```
df.shape
```

```
(9527, 5)
```



VISUALIZATIONS

CHECKING FOR OUTLIERS USING BOXPLOT





REMOVING OUTLIERS USING IQR METHOD

```
# Calculating IQR
IQR_amb = 1017.20 - 1009.08
IQR_r = 84.85 - 63.37
#printing
print("IQR for amb_pressure is: ",IQR_amb)
print("IQR for r_humidity is: ",IQR_r)

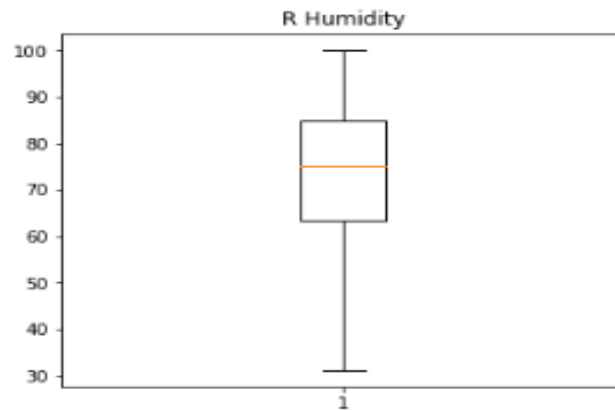
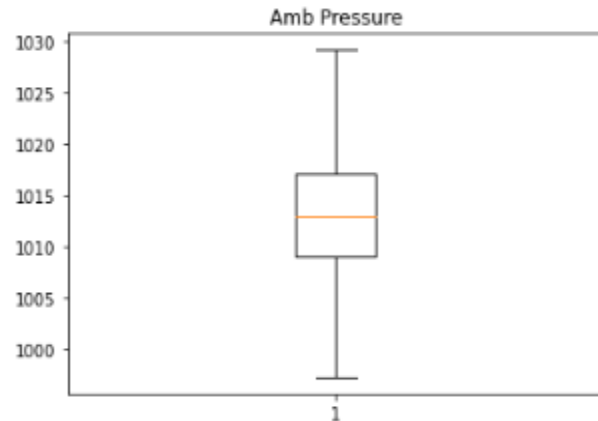
#Calculating Lower & Upper Extreme for amb_pressure
LE_amb = 1009.08 - IQR_amb * 1.5
UE_amb = 1017.20 + IQR_amb * 1.5
#printing
print("Lower Extreme of amb_pressure is: ",LE_amb)
print("Upper Extreme of amb_pressure is: ",UE_amb)

#Calculating Lower & Upper Extreme for r_humidity
LE_r = 63.37 - IQR_r * 1.5
UE_r = 84.85 + IQR_r * 1.5
#printing
print("Lower Extreme of r_humidity is: ",LE_r)
print("Upper Extreme of r_humidity is: ",UE_r)

IQR for amb_pressure is: 8.120000000000005
IQR for r_humidity is: 21.479999999999997
Lower Extreme of amb_pressure is: 996.9000000000001
Upper Extreme of amb_pressure is: 1029.38
Lower Extreme of r_humidity is: 31.15
Upper Extreme of r_humidity is: 117.07
```



AFTER REMOVING OUTLIERS



Inference : There are No more Outliers present in the dataset



FINAL DATA SET AFTER EDA

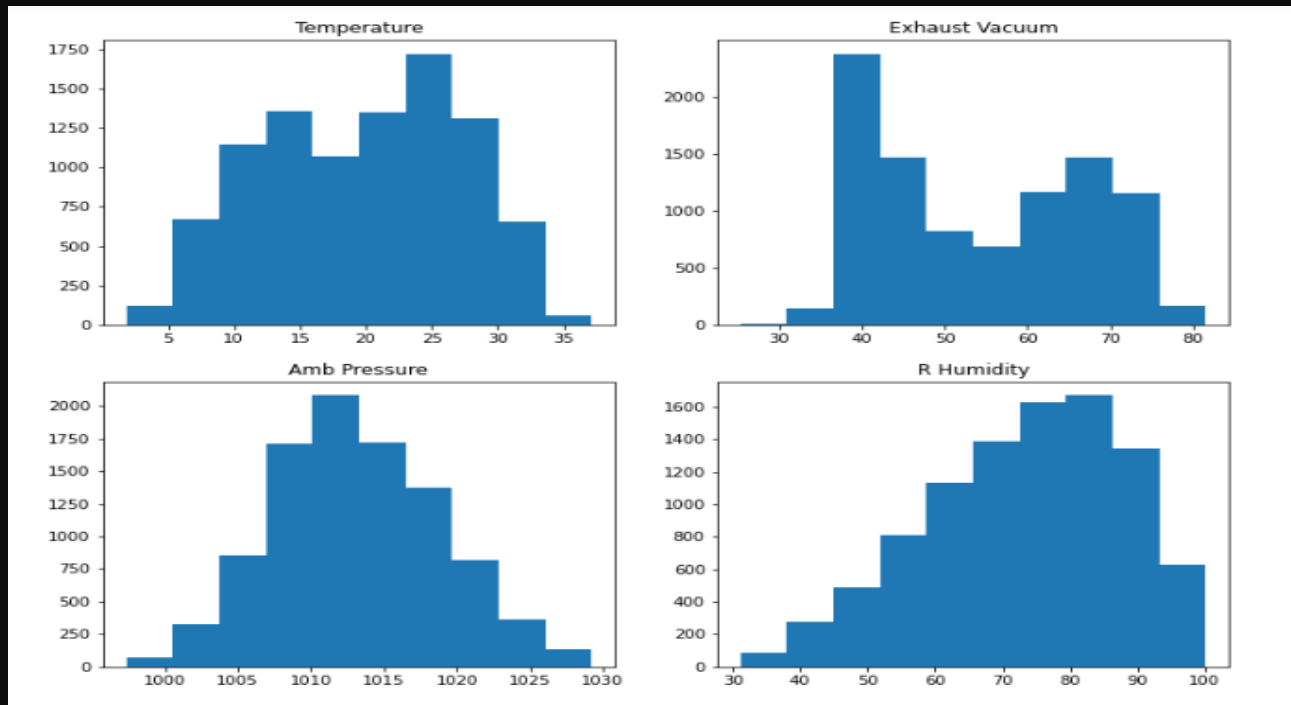
In [24]: *# Final Dataset after EDA*
df5.head()

Out[24]:

| | temperature | exhaust_vacuum | amb_pressure | r_humidity | energy_production |
|---|-------------|----------------|--------------|------------|-------------------|
| 0 | 9.59 | 38.56 | 1017.01 | 60.10 | 481.30 |
| 1 | 12.04 | 42.34 | 1019.72 | 94.67 | 465.36 |
| 2 | 13.87 | 45.08 | 1024.42 | 81.69 | 465.48 |
| 3 | 13.72 | 54.30 | 1017.89 | 79.08 | 467.05 |
| 4 | 15.14 | 49.64 | 1023.78 | 75.00 | 463.58 |

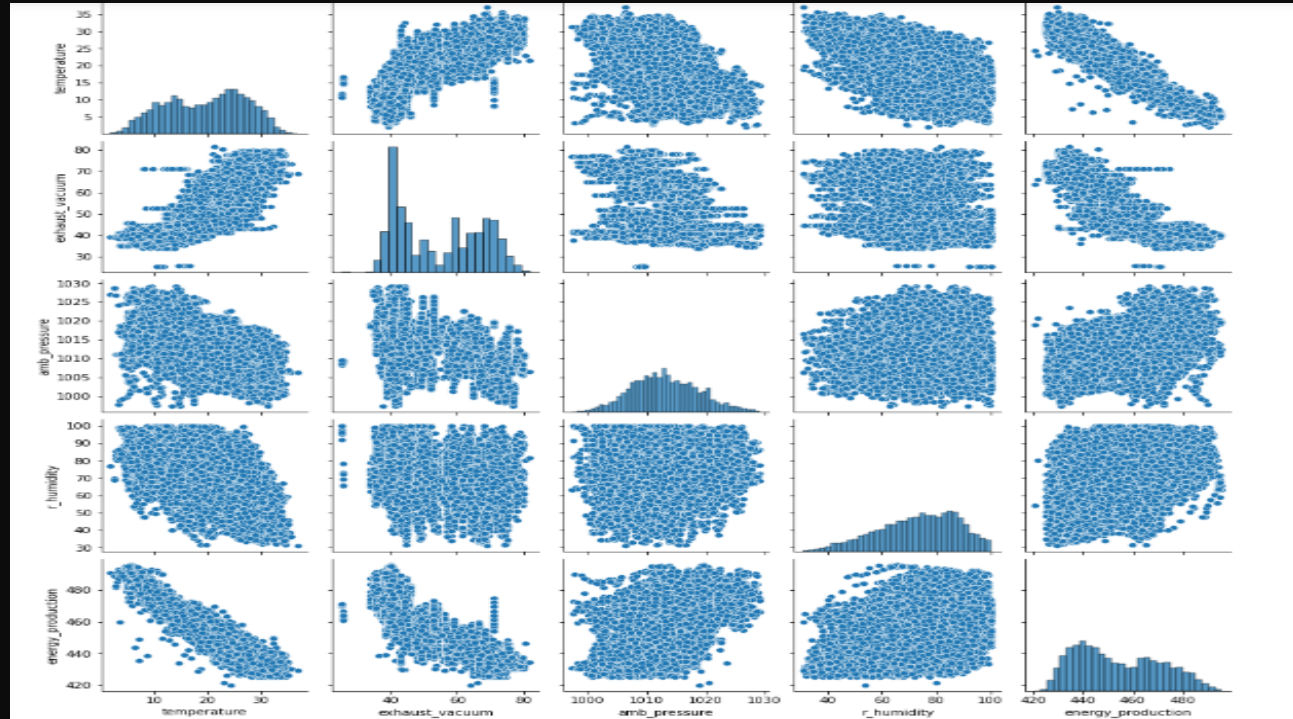


HISTOGRAM PLOT





CHECKING COLLINEARITY B/W INDEPENDENT VARIABLES





Inference:

As we can see "temperature" & "exhaust_vacuum" have a strong positive Correlation, So we can say that there is a multicollinearity effect present.

```
In [27]: df5.corr()
```

```
Out[27]:
```

| | temperature | exhaust_vacuum | amb_pressure | r_humidity | energy_production |
|-------------------|-------------|----------------|--------------|------------|-------------------|
| temperature | 1.000000 | 0.842728 | -0.508625 | -0.542175 | -0.947491 |
| exhaust_vacuum | 0.842728 | 1.000000 | -0.415389 | -0.310217 | -0.868693 |
| amb_pressure | -0.508625 | -0.415389 | 1.000000 | 0.105210 | 0.521194 |
| r_humidity | -0.542175 | -0.310217 | 0.105210 | 1.000000 | 0.388023 |
| energy_production | -0.947491 | -0.868693 | 0.521194 | 0.388023 | 1.000000 |



CROSS CHECK WITH VIF

```
In [28]: rsq_Tem = smf.ols('temperature~exhaust_vacuum+amb_pressure+r_humidity',data=df5).fit().rsquared
vif_Tem = 1/(1-rsq_Tem)

rsq_ex = smf.ols('exhaust_vacuum~temperature+amb_pressure+r_humidity',data=df5).fit().rsquared
vif_ex = 1/(1-rsq_ex)

rsq_amb = smf.ols('amb_pressure~temperature+exhaust_vacuum+r_humidity',data=df5).fit().rsquared
vif_amb = 1/(1-rsq_amb)

rsq_rh = smf.ols('r_humidity~temperature+exhaust_vacuum+amb_pressure',data=df5).fit().rsquared
vif_rh = 1/(1-rsq_rh)

# Storing vif values in a data frame
d1 = {'Variables':['temperature','exhaust_vacuum','amb_pressure','r_humidity'],'VIF':[vif_Tem,vif_ex,vif_amb,vif_rh]}
Vif_frame = pd.DataFrame(d1)
Vif_frame
```

```
Out[28]:
```

| | Variables | VIF |
|---|----------------|----------|
| 0 | temperature | 5.906452 |
| 1 | exhaust_vacuum | 3.907032 |
| 2 | amb_pressure | 1.447254 |
| 3 | r_humidity | 1.696703 |

Inference - There is no multi-collinearity between the variables , since VIF is less than 20.



OVERVIEW REPORT OF EDA

```
In [52]: EDA_report= pp.ProfileReport(df5)
EDA_report.to_file(output_file='report.html')

Summarize dataset: 0%|          | 0/5 [00:00<?, ?it/s]
Generate report structure: 0%|          | 0/1 [00:00<?, ?it/s]
Render HTML: 0%|          | 0/1 [00:00<?, ?it/s]
Export report to file: 0%|          | 0/1 [00:00<?, ?it/s]
```

In []:

```
In [31]: df5
```

```
Out[31]:
```

| | temperature | exhaust_vacuum | amb_pressure | r_humidity | energy_production |
|------|-------------|----------------|--------------|------------|-------------------|
| 0 | 9.59 | 38.56 | 1017.01 | 60.10 | 481.30 |
| 1 | 12.04 | 42.34 | 1019.72 | 94.67 | 465.36 |
| 2 | 13.87 | 45.08 | 1024.42 | 81.69 | 465.48 |
| 3 | 13.72 | 54.30 | 1017.89 | 79.08 | 467.05 |
| 4 | 15.14 | 49.64 | 1023.78 | 75.00 | 463.58 |
| ... | ... | ... | ... | ... | ... |
| 9563 | 17.10 | 49.69 | 1005.53 | 81.82 | 457.32 |
| 9564 | 24.73 | 65.34 | 1015.42 | 52.80 | 446.92 |
| 9565 | 30.44 | 56.24 | 1005.19 | 56.24 | 429.34 |
| 9566 | 23.00 | 66.05 | 1020.61 | 80.29 | 421.57 |
| 9567 | 17.75 | 49.25 | 1020.86 | 63.67 | 454.41 |

9461 rows × 5 columns

INFERENCE

- Original data set contains - 9568 observations

- Duplicates – 41 observations

- After Removal of Duplicates - 9527 observations

- After Removal of Outliers - 9417

Final Data set Contains – 9418 Observations

MODEL BUILDING

MODELS USED FOR MODEL BUILDING -



LINEAR REGRESSION



ADABOOST REGRESSOR



LASSO AND RIDGE REGRESSION



KNN MODEL



DECISION TREE REGRESSION



XGBoost Regressor



RANDOM FOREST REGRESSION

01. LINEAR MODEL

SPLITTING X and Y

```
#Splitting X & Y Variable
# X Variable
X = df5.drop(['energy_production'], axis = 'columns')
# Y Variable
Y = df5.energy_production
#printing shape of both
print("X :",X.shape)
print("Y :",len(Y))
```

```
X : (9417, 4)
Y : 9417
```

```
X_train.shape
```

```
(7533, 4)
```

```
X_test.shape
```

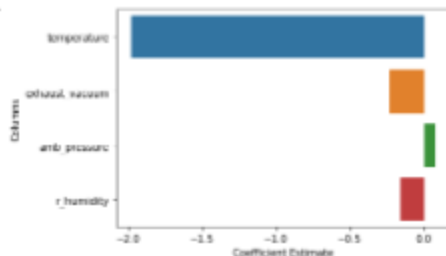
```
(1884, 4)
```

Linear model

```
#Model
Lmodel = LinearRegression()
Lmodel.fit(X_train,Y_train)
Lmodel.score(X_test,Y_test)*100
```

```
92.50970525865723
```

<AxesSubplot:xlabel='Coefficient Estimate', ylabel='Columns'>



02. LASSO & REGRESSION

```
# Ridge regression
from sklearn.linear_model import Ridge

# Train the model
ridgeR = Ridge(alpha = 1)
ridgeR.fit(X_train, Y_train)
y_pred = ridgeR.predict(X_test)

# calculate mean square error
mean_squared_error_ridge = np.mean((y_pred - Y_test)**2)
print("Mean_Squared_error:", mean_squared_error_ridge)

# get ridge coefficient and print them
ridge_coefficient = pd.DataFrame()
ridge_coefficient["Columns"] = X_train.columns
ridge_coefficient['Coefficient Estimate'] = pd.Series(ridgeR.coef_)
print(ridge_coefficient)
```

```
Mean_Squared_error: 21.01452500349596
   Columns  Coefficient Estimate
0  temperature          -1.976951
1 exhaust_vacuum          -0.230662
2   amb_pressure           0.080297
3    r_humidity          -0.160455
```

```
# Lasso Regression
from sklearn.linear_model import Lasso

# Train the model
lasso = Lasso(alpha = 1)
lasso.fit(X_train, Y_train)
y_pred1 = lasso.predict(X_test)

# Calculate Mean Squared Error
mean_squared_error = np.mean((y_pred1 - Y_test)**2)
print("Mean squared error on test set", mean_squared_error)
lasso_coeff = pd.DataFrame()
lasso_coeff["Columns"] = X_train.columns
lasso_coeff['Coefficient Estimate'] = pd.Series(lasso.coef_)

print(lasso_coeff)
```

```
Mean squared error on test set 21.021888475894897
   Columns  Coefficient Estimate
0  temperature          -1.921902
1 exhaust_vacuum          -0.248816
2   amb_pressure           0.064529
3    r_humidity          -0.144717
```

03. DECISION TREE REGRESSOR

```
# Decision Tree Regressor
seed = 7
kfold = KFold(n_splits=10, random_state=seed, shuffle=True)
cart = DecisionTreeRegressor()
num_trees = 100
model = BaggingRegressor(base_estimator=cart, n_estimators=num_trees, random_state=seed)
results = cross_val_score(model, X_train, Y_train, cv=kfold)
print(results.mean())
```

0.9599123064600011

04. RANDOM FOREST REGRESSOR

```
# Random Forest Regressor
num_trees = 100
max_features = 3
kfold = KFold(n_splits=10, random_state=7, shuffle=True)
model = RandomForestRegressor(n_estimators=num_trees, max_features=max_features)
results = cross_val_score(model, X_train, Y_train, cv=kfold)
print(results.mean())

0.9607671535736031
```

05. ADABOOST REGRESSOR

```
# Adaboost Regressor
num_trees = 10
seed=7
kfold = KFold(n_splits=10, random_state=seed,shuffle=True)
model = AdaBoostRegressor(n_estimators=num_trees, random_state=seed)
results = cross_val_score(model, X_train, Y_train, cv=kfold)
print(results.mean())
```

0.9075739194628539

06. XGBOOST REGRESSOR

```
F_model = XGBRegressor(n_estimators=250, learning_rate=0.2, max_depth=5)  
F_model.fit(X_train, Y_train)  
F_model.score(X_test, Y_test)*100
```

96.30225774714421

07. KNN MODEL

```
n_neighbors = np.array(range(1,41))
param_grid = dict(n_neighbors=n_neighbors)
model = KNeighborsRegressor()
grid = GridSearchCV(estimator=model,param_grid=param_grid)
grid.fit(X_train,Y_train)
print(grid.best_score_)
print(grid.best_params_)
```

```
0.9436345358354734
{'n_neighbors': 5}
```

```
KNN_model = KNeighborsRegressor(n_neighbors=5)
KNN_model.fit(X_train,Y_train)
```

```
KNeighborsRegressor()
```

```
Y_pred = KNN_model.predict(X_test)
KNN_1 = metrics.explained_variance_score(Y_test,Y_pred)
print("Accuracy:" ,KNN_1)
```

```
Accuracy: 0.9443999431784652
```



CHOOSING THE BEST MODEL FOR DEPLOYMENT

```
In [45]: def find_best_model_using_gridsearchcv(x,y):
        algos = {
            'linear_regression': {'model': LinearRegression(), 'params': {'normalize': [False]}},
            },
            'ridge': {'model': Ridge(), 'params': {'alpha': [0.1, 0.1, 0.5, 1]}},
            },
            'lasso': {'model': Lasso(), 'params': {'alpha': [0.1, 0.5, 1], 'selection': ['random', 'cyclic']}},
            },
            'decision_tree': {'model': DecisionTreeRegressor(), 'params': {'criterion': ['mse', 'friedman_mse'], 'splitter': ['best',
            ],
            'Random Forest': {'model': RandomForestRegressor(), 'params': {'n_estimators': [100, 125, 150, 200], 'max_features': [3, 4]}},
            },
            'XGBoost': {'model': XGBRegressor(), 'params': {'n_estimators': [100, 125, 150, 200, 225, 250], 'max_depth': [3, 4, 5], 'learning
            },
            'SVM': {'model': SVR(), 'params': {'kernel': ['rbf']}},
            },
            'KNN': {'model': KNeighborsRegressor(), 'params': {'n_neighbors': [5, 10, 15, 20, 25, 30, 35, 40, 45, 50]}},
            }
        scores = []
        cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=10)
        for algo_name, config in algos.items():
            gs = GridSearchCV(config['model'], config['params'], cv=cv)
            gs.fit(x,y)
            scores.append({
                'model': algo_name,
                'best_score': gs.best_score_,
                'best_params': gs.best_params_
            })

        return pd.DataFrame(scores, columns=['model', 'best_score', 'best_params'])

find_best_model_using_gridsearchcv(X,Y)
```

THE FINAL MODEL CHOSEN -

RANDOM FOREST MODEL

| | model | best_score | best_params |
|---|-------------------|------------|---|
| 0 | linear_regression | 0.929326 | {'normalize': False} |
| 1 | ridge | 0.929326 | {'alpha': 1} |
| 2 | lasso | 0.929328 | {'alpha': 0.1, 'selection': 'random'} |
| 3 | decision_tree | 0.924775 | {'criterion': 'friedman_mse', 'splitter': 'best'} |
| 4 | Random Forest | 0.962977 | {'max_features': 3, 'n_estimators': 200} |
| 5 | XGBoost | 0.966608 | {'learning_rate': 0.2, 'max_depth': 5, 'n_esti... |
| 6 | SVM | 0.376926 | {'kernel': 'rbf'} |
| 7 | KNN | 0.945204 | {'n_neighbors': 5} |



ACCURACY – 96.29%

