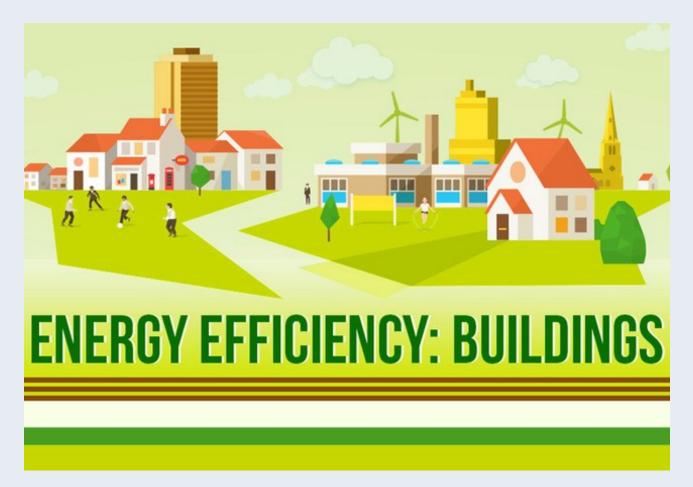
6. 냉난방 부하예측 머신러닝모델 개발

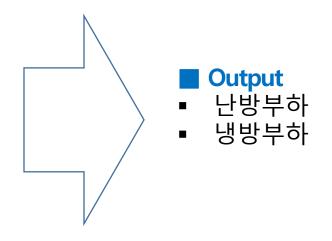


건물 에너지 소비는 전체 에너지 사용의 약 40%를 차지합니다.

설계 단계에서 건물의 냉난방 부하를 예측하는 것은 에너지 효율화를 위해 매우 중요합니다. 건물 에너지 성능에 대한 데이터셋을 기반으로 건물의 냉난방 부하를 예측하는 다양한 모델을 개발합니다.

Input

- Relative Compactness
- Surface Area m²
- Wall Area m²
- Roof Area m²
- Overall Height m
- Orientation 2:North, 3:East, 4:South, 5:West
- Glazing Area 0%, 10%, 25%, 40% (of floor area)
- Glazing Area Distribution (Variance)
 - 1:Uniform, 2:North, 3:East, 4:South, 5:West
- Heating Load kWh
- Cooling Load kWh





energy_efficiency_modeling.ipynb

```
[1] import os
   import numpy as np
   import pandas as pd
   import matplotlib.pyplot as plt
   import seaborn as sns
   import warnings
   warnings.filterwarnings('ignore')
[2] data = pd.read_csv('building_energy_efficiency.csv')
```

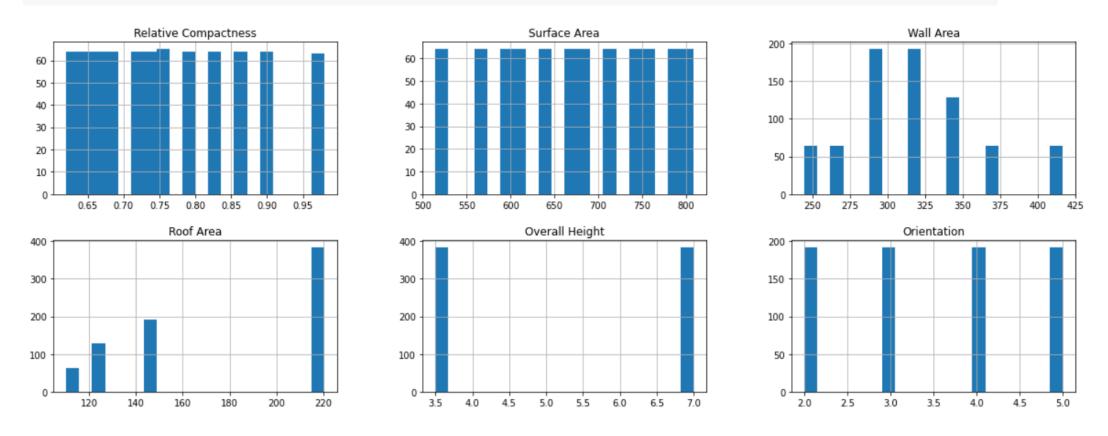
[3] data.head()

	Relative Compactness	Surface Area	Wall Area	Roof Area	Overall Height	Orientation	Glazing Area	Glazing Area Distribution	Heating Load	Cooling Load
0	0.7638	514.5	294.0	110.25	7.0	2	0.0	0	15.55	21.33
1	0.9800	514.5	294.0	110.25	7.0	3	0.0	0	15.55	21.33
2	0.9800	514.5	294.0	110.25	7.0	4	0.0	0	15.55	21.33
3	0.9800	514.5	294.0	110.25	7.0	5	0.0	0	15.55	21.33
4	0.9000	563.5	318.5	122.50	7.0	2	0.0	0	20.84	28.28

```
[4] data.shape
    (768, 10)
[5]
    data.isnull().sum()
    Relative Compactness
    Surface Area
    Wall Area
    Roof Area
    Overall Height
    Orientation
    Glazing Area
    Glazing Area Distribution
                                  0
    Heating Load
    Cooling Load
    dtype: int64
```

각 데이터의 분포 체크

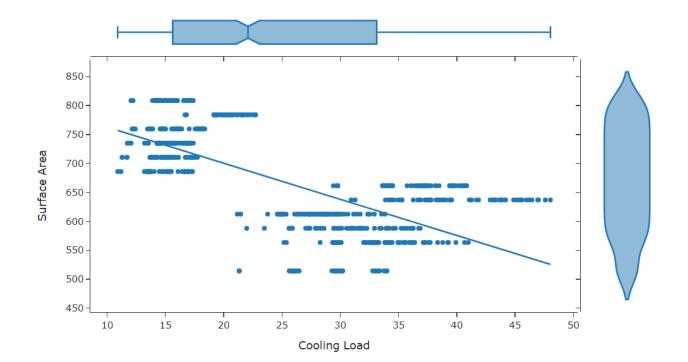
[6] data.hist(bins=20, figsize=(20,15))
plt.show()



상관관계 분석

```
[7] import plotly.express as px

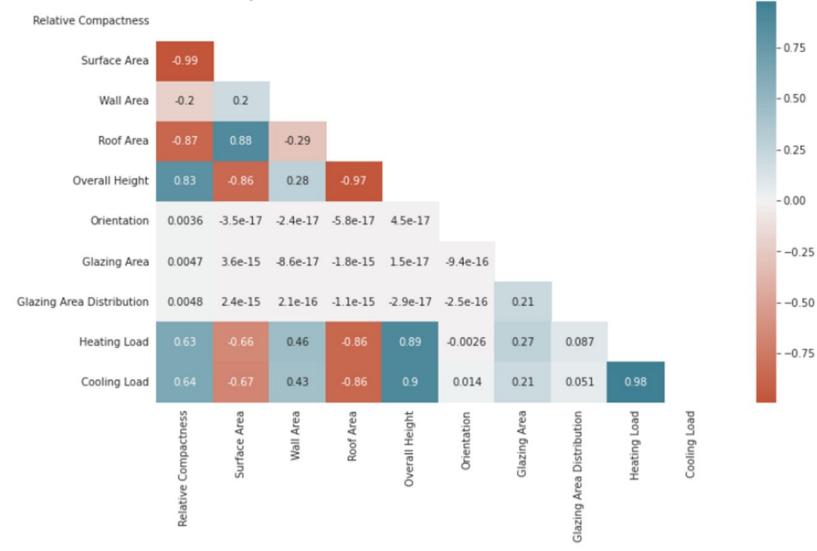
yprop = 'Surface Area'
xprop = 'Cooling Load'
h= None
px.scatter(data, x=xprop, y=yprop, color=h, marginal_y="violin", marginal_x="box", trendline="ols",
```



명확한 상관관계를 찾기위해 상관관계 행렬 확인

```
[9]
    import matplotlib.pyplot as plt
     import matplotlib.style as style
     import seaborn as sns
    style.use('ggplot')
    sns.set_style('whitegrid')
    plt.subplots(figsize = (12,7))
    ## Plotting heatmap. # Generate a mask for the upper triangle (taken from seabor
    mask = np.zeros_like(data.corr(), dtype=np.bool)
    mask[np.triu_indices_from(mask)] = True
    sns.heatmap(data.corr(), cmap=sns.diverging_palette(20, 220, n=200), annot=True,
    plt.title("Heatmap of all the Features of Train data set", fontsize = 25);
```

Heatmap of all the Features of Train data set



```
[11] from scipy.stats import randint as sp_randint
     from catboost import CatBoostRegressor
     from sklearn.model_selection import GridSearchCV
     from keras. Layers import Dense
     from keras.models import Sequential
     from sklearn.tree import DecisionTreeRegressor
     from sklearn.neighbors import KNeighborsRegressor
     from sklearn.neural_network import MLPRegressor
     from sklearn.ensemble import GradientBoostingRegressor,AdaBoostRegressor
     from sklearn.ensemble import BaggingRegressor, RandomForestRegressor
     from sklearn.model selection import GridSearchCV
     from sklearn.model_selection import train_test_split
     from sklearn.multioutput import MultiOutputRegressor
     from sklearn.preprocessing import MinMaxScaler
     from sklearn.svm import SVC
     from sklearn.svm import SVR
     from sklearn.metrics import accuracy_score, f1_score
     from sklearn.metrics import r2_score
     from sklearn.metrics import roc auc score
```

- 데이터 세트를 훈련 및 테스트 세트로 분할.
- 특징 스케일링 또는 데이터 정규화는 데이터의 독립 변수
 또는 특징의 범위를 정규화하는 데 사용되는 방법입니다.
- 따라서 독립 변수에서 값이 많이 다를 때 모든 값이
 비교 가능한 범위에 유지되도록 특성 스케일링을 사용합니다.

생난방 부하 예측모델 모델링

각 모델의 결과를 저장할 DataFrame을 만듭니다.

```
[16] for r in regressors:
         name = r[0]
         model = r[1]
         model.fit(X train, y1 train)
         actr1 = r2_score(y1_train, model.predict(X_train))
         acte1 = r2_score(y1_test, model.predict(X_test))
         model.fit(X train, y2 train)
         actr2 = r2_score(y2_train, model.predict(X_train))
         acte2 = r2_score(y2_test, model.predict(X_test))
         accuracy = accuracy.append(pd.Series({'model':name, 'train_Heating':actr1,
                                     'test_Heating':acte1,'train_Cooling':actr2,
                                     'test Cooling':acte2}),ignore index=True )
     accuracy.sort_values(by='test_Cooling')
```

	model	train_Heating	test_Heating	train_Cooling	test_Cooling
4	MLPRegressor	0.866251	0.874380	0.808819	0.831392
0	SVR	0.930662	0.910593	0.892578	0.887385
2	KNeighborsRegressor	0.945989	0.904490	0.926869	0.888896
1	DecisionTreeRegressor	1.000000	0.995243	1.000000	0.948064
5	AdaBoostRegressor	0.970024	0.964384	0.946378	0.948302
3	Random Forest Regressor	0.999497	0.997359	0.995431	0.964139
6	Gradient Boosting Regressor	0.998173	0.997641	0.979423	0.976044

모델 파라미터 튜닝

- Boosting machine learning 알고리즘은 단순한 알고리즘보다 더 나은 정확도를 제공하기 때문에 많이 사용됩니다.
- 알고리즘의 성능은 하이퍼파라미터에 따라 다릅니다.
- 최적의 parameter는 더 높은 정확도를 달성하는 데 도움이 될 수 있습니다.
- 수동으로 hyper parameter를 찾는 것은 지루하고 계산 비용이 많이 듭니다.
- 하이퍼파라미터 튜닝의 자동화가 중요합니다.
- RandomSearch, GridSearchCV, Bayesian optimization은 하이퍼파라미터를 최적화하는 데 사용됩니다.

```
[17] param_grid = [{"learning_rate": [0.01, 0.02, 0.1],
                    "n_estimators":[150, 200, 250], "max_depth": [4, 5, 6],
                     "min_samples_split":[1, 2, 3], "min_samples_leaf":[2, 3],
                    "subsample":[1.0, 2.0]}]
     gb = GradientBoostingRegressor()
     gs_gb = GridSearchCV(gb, param_grid, cv=10,
                         scoring='neg_mean_squared_error')
     gs_gb.fit(X_train, y2_train)
     print("R-Squared : {}".format(gs_gb.best_score_))
     print(f"Best Hyperparameters : ₩n{gs gb.best params }")
     R-Squared : -1.0361285669594182
     Best Hyperparameters :
     {'learning_rate': 0.1, 'max_depth': 5, 'min_samples_leaf': 3, 'min_samples_split': 3,
```

A. Decision Tree Regressor parameters turning

```
[18] dt = DecisionTreeRegressor()
     param_grid = {"criterion": ["squared_error", "absolute_error"],"min_samples_spli|t": [15, 10
                    "max_depth": [5, 6, 7],"min_samples_leaf": [4, 5, 6],
                    "max_leaf_nodes": [29, 30, 31, 32],}
     gs_dt = GridSearchCV(dt, param_grid, cv=5)
     gs dt.fit(X train, y2 train)
     print(f"R-Squared : {gs_dt.best_score_}")
     print(f"Best Hyperparameters : ₩n{gs dt.best params }")
     R-Squared : 0.959889622709387
     Best Hyperparameters:
     {'criterion': 'squared_error', 'max_depth': 6, 'max_leaf_nodes': 30, 'min_samples_leaf': 5
```

R-Squared on train dataset=0.9953559923756888 R-Squaredon test dataset=0.9592409931240966

B. Tune Random Forests Parameters

```
[20] from sklearn.model_selection import GridSearchCV
     param_grid = [\{'n_estimators': [350, 400, 450], 'max_features': [1, 2],
                     'max_depth': [85, 90, 95]}]
     rf = RandomForestRegressor(n jobs=-1)
     gs rf = GridSearchCV(rf, param grid, cv=10,
                          scoring='neg_mean_squared_error')
     gs_rf.fit(X_train, y2_train)
     print(f"R-Squared::{gs_rf.best_score_}")
     print(f"Best Hyperparameters::\munitum {gs_rf.best_params_}")
     R-Squared::-2.704375462246052
     Best Hyperparameters::
     {'max_depth': 95, 'max_features': 1, 'n_estimators': 450}
```

```
[21] rf = RandomForestRegressor(n_estimators=250, max_features=1,
                                max_depth=90, bootstrap=True)
     rf.fit(X_train,y1_train)
     print("R-Squared on train dataset={}".format(rf.score(X_test,y1_test)))
     rf.fit(X_train,y2_train)
     print(f"R-Squaredon test dataset={rf.score(X_test,y2_test)}")
     R-Squared on train dataset=0.9910854073670696
     R-Squaredon test dataset=0.9743420800363577
```

C. Gradient Boosting Regression - Hyperparameter Tuning

R-Squared on train dataset=0.9986719997364437 R-Squaredon test dataset=0.9915692478361576

D. CatBoostRegressor

```
import warnings
warnings.filterwarnings("ignore")
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.model selection import GridSearchCV
from catboost import CatBoostRegressor
cb = CatBoostRegressor()
parameters = \{ \text{'depth'} : [8, 10], \text{'iterations'} : [10000], \text{'learning rate'} : [0.02, 0.03], \}
               'border count':[5], 'random state': [42, 45]}
gs_cb = GridSearchCV(estimator=cb, param_grid = parameters, cv = 2, n_jobs=-1)
gs cb.fit(X train, y2 train)
print("Results from Grid Search" )
print(f"\n The best estimator across ALL searched params:\n{gs_cb.best_estimator_}")
print(f"\n The best score across ALL searched params:\n{gs_cb.best_score_}")
```

[24] print(f"\n The best parameters across ALL searched params:\n{gs_cb.best_params_}\")

The best parameters across ALL searched params: {'border_count': 5, 'depth': 10, 'iterations': 10000, 'learning_rate': 0.02, 'random_state': 4

모델 성능 Summary

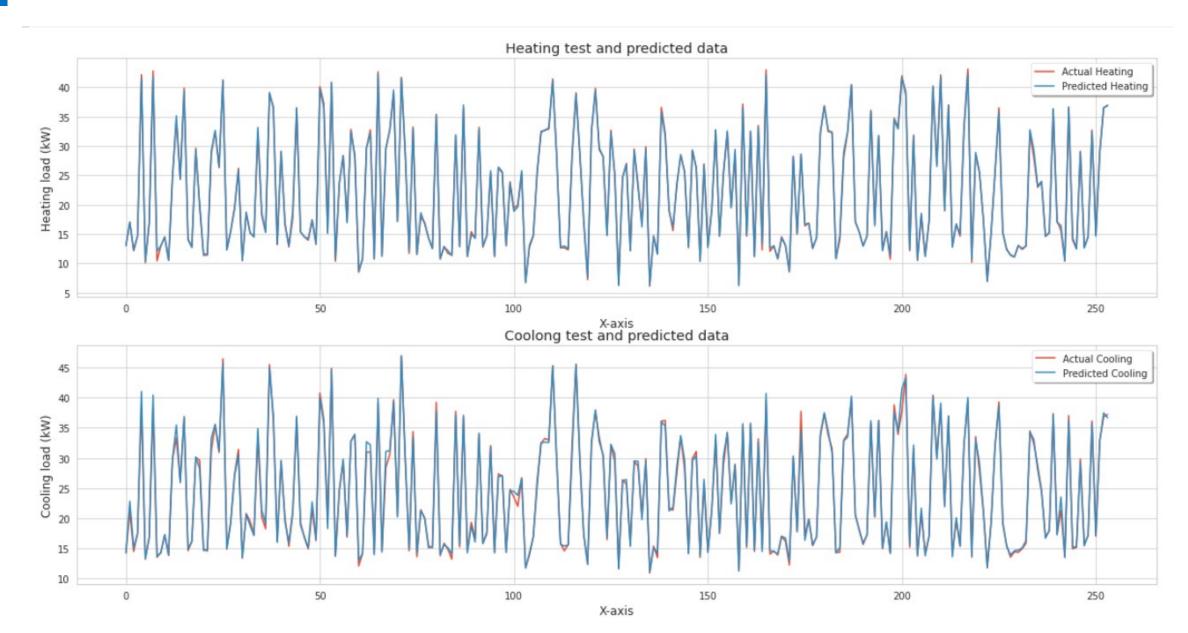
```
[25] accuracy = pd.DataFrame(index=None, columns=['model',
                                        'train_Heating', 'test_Heating',
                                        'train_Cooling', 'test_Cooling'])
[26] regressors = [
          ["DecisionTreeRegressor",
              DecisionTreeRegressor(
                  criterion='squared_error', max_depth=6, max_leaf_nodes=31,
                  min_samples_leaf=5, min_samples_split=17
          ["RandomForestRegressor",
              RandomForestRegressor(
                  max_depth=85, max_features=1, n_estimators=350
          ["GradientBoostingRegressor",
              GradientBoostingRegressor(
                  learning_rate=0.1, n_estimators=250, max_depth=5,
                  min_samples_split=2, min_samples_leaf=3, subsample=1.0,
          ["CatBoostRegressor",
              CatBoostRegressor(
                  border_count=5, depth=10, iterations=10000,
                  learning_rate=0.02, random_state=42
```

- 난방 및 냉방 부하를 예측하기 위해 다양한 모델을 사용하여 건물 에너지 성능을 예측 했습니다.
- 모델에서 다양한 parameter를 조정하여 매우 좋은 예측 결과를 얻었습니다.
- 난방 및 냉방 부하 모두에서 >99.5%, 실험 데이터 세트와 비교

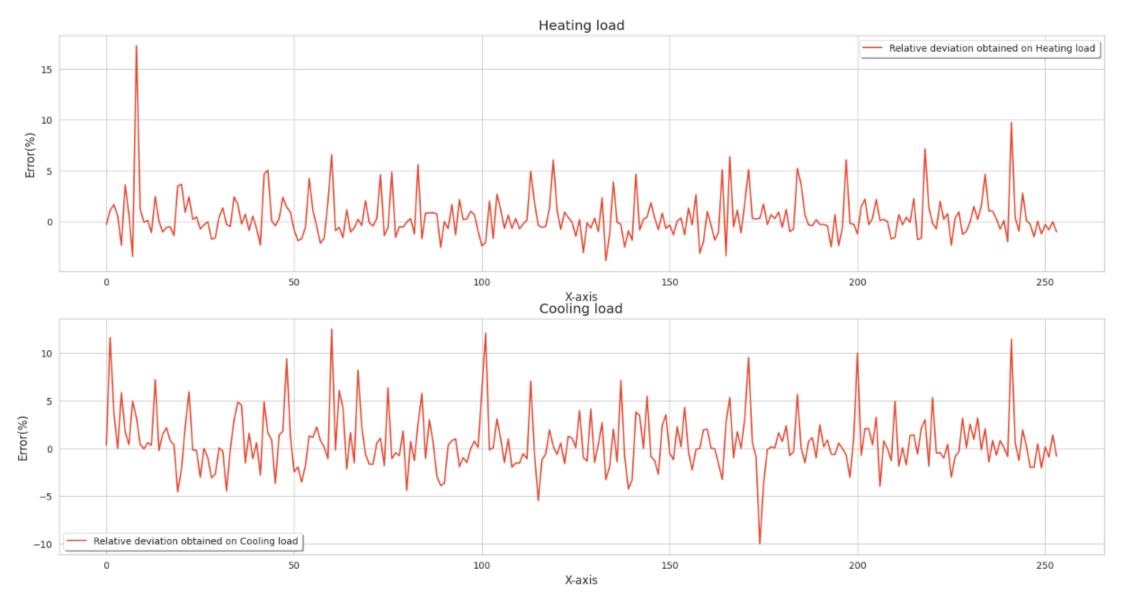
```
[28] best_model = CatBoostRegressor(border_count=5, depth=10, iterations=10000,
                               learning rate=0.02, random state=42)
     best model.fit(X train,y1 train)
     actr1 = r2_score(y1_train, best_model.predict(X_train))
     acte1 = r2_score(y1_test, best_model.predict(X_test))
     y1_pred = best_model.predict(X_test)
     best model.fit(X train,y2 train)
     actr2 = r2_score(y2_train, best_model.predict(X_train))
     acte2 = r2_score(y2_test, best_model.predict(X_test))
     y2 pred = best model.predict(X test)
```

	model	train_Heating	test_Heating	train_Cooling	test_Cooling
0	Decision Tree Regressor	0.994874	0.995248	0.967755	0.959161
1	Random Forest Regressor	0.998717	0.991695	0.996149	0.972668
2	Gradient Boosting Regressor	0.999735	0.998552	0.998988	0.991906
3	CatBoostRegressor	1.000000	0.998466	1.000000	0.993174

```
[30] x_{ax} = range(len(y1_test))
     plt.figure(figsize=(20,10))
     plt.subplot(2,1,1)
     plt.plot(x ax, y1 test, label="Actual Heating")
     plt.plot(x_ax, y1_pred, label="Predicted Heating")
     plt.title("Heating test and predicted data")
     plt.xlabel('X-axis')
     plt.ylabel('Heating load(kW)')
     plt.legend(loc='best',fancybox=True, shadow=True)
     plt.grid(True)
     plt.subplot(2,1,2)
     plt.plot(x ax, y2 test, label="Actual Cooling")
     plt.plot(x_ax, y2_pred, label="Predicted Cooling")
     plt.title("Coolong test and predicted data")
     plt.xlabel('X-axis')
     plt.ylabel('Cooling load(kW)')
     plt.legend(loc='best',fancybox=True, shadow=True)
     plt.grid(True)
     plt.show()
```



```
[31] def calculate error rate(y1 test, y1 pred):
         error_rate=[]
         for i in range(len(y1 pred)):
             error rate.append((y1 pred[i] - y1 test.values[i])/y1 test.values[i]*100)
         return error rate
[32] x ax = range(len(y1 test))
     plt.figure(figsize=(20,10))
     plt.subplot(2,1,1)
     plt.plot(x_ax, calculate_error_rate(y1_test, y1_pred),
              label="Relative deviation obtained on Heating load")
     plt.title("Heating load")
     plt.xlabel('X-axis')
     plt.ylabel('Error(%)')
     plt.legend(loc='best',fancybox=True, shadow=True)
     plt.grid(True)
     plt.subplot(2.1.2)
     plt.plot(x ax, calculate error rate(y2 test, y2 pred),
              label="Relative deviation obtained on Cooling load")
     plt.title("Cooling load")
     plt.xlabel('X-axis')
     plt.ylabel('Error(%)')
     plt.legend(loc='best',fancybox=True, shadow=True)
     plt.grid(True)
     plt.show()
```



THANK YOU

kgpark88@gmail.com