data preprocess

```
import numpy as np
import pandas as pd
```

```
# load data
data = {}
file_name = ['202212', '202301', '202302']

for f in file_name:
  data[f] =
pd.read_excel("/content/drive/MyDrive/Project/cqu_ds_exp/data/"+f+".xlsx"); #
dataframe
```

```
# delete invalid column
def delete_invalid_column(invalid_cols, data):
  for invalid_col in invalid_cols:
    if invalid_col in data:
      data.drop([invalid_col], axis=1, inplace=True)

del_col = ['序号', '是否离线', '设备状态']
for f in file_name:
  delete_invalid_column(del_col, data[f])
```

```
# caculate the numeber of empty row
empty_rows_number = 0
def cal_empty_row_num(data):
  empty_rows = data[data.isna().all(axis=1)]
  return len(empty_rows)

for f in file_name:
  empty_rows_number += cal_empty_row_num(data[f])

print(empty_rows_number)
```

```
259
```

```
# delete empty row
for f in file_name:
  data[f] = data[f].dropna(how='all')
```

```
# caculate the number of row that has empty value
total_empty_val_row_num = 0
def cal_empty_val_row(data):
  return data.isna().any(axis=1).sum()

for f in file_name:
  total_empty_val_row_num += cal_empty_val_row(data[f])

print(total_empty_val_row_num)
```

```
71
```

```
# delete rows that hav empty value
for f in file_name:
  data[f] = data[f].dropna()
```

```
# concat
total_data = pd.concat([data[f] for f in file_name], axis=0)
```

```
print(total_data.dtypes)
```

```
所属杆塔        object
测量时间        object
气温          float64
空气湿度        float64
风速          float64
风向          float64
气压          float64
降雨量         float64
覆冰厚度        float64
覆冰占比        float64
拉力值         float64
辐射          float64
覆冰告警等级      float64
预警等级        object
dtype: object
```

```
# data type trans
total_data['测量时间'] = pd.to_datetime(total_data['测量时间'])
total_data['所属杆塔'] = total_data['所属杆塔'].astype(str)
total_data['预警等级'] = total_data['预警等级'].astype(str)
total_data['覆冰告警等级'] = total_data['覆冰告警等级'].astype(int)
print(total_data.dtypes)
```

```
所属杆塔                 object
测量时间        datetime64[ns]
气温                  float64
空气湿度                float64
```

```
风速                float64
风向                float64
气压                float64
降雨量               float64
覆冰厚度              float64
覆冰占比              float64
拉力值               float64
辐射                float64
覆冰告警等级              int64
预警等级              object
dtype: object
```

```
# delete duplicated row
total_data.drop_duplicates(keep='last', inplace=True)
```

```
print(total_data['覆冰告警等级'].drop_duplicates())
print(total_data['预警等级'].drop_duplicates())
```

```
0      0
1      2
955    4
964    3
730    1
821    6
869    5
Name: 覆冰告警等级, dtype: int64
0        正常
1      橙色预警
267    黄色预警
342    红色预警
Name: 预警等级, dtype: object
```

```
# group
data_62 = total_data[total_data['所属杆塔'] == '62#']
data_99 = total_data[total_data['所属杆塔'] == '99#']
print(data_62.shape[0])
print(data_99.shape[0])
```

```
1864
2064
```

```
# 62# is useless for prediction
print(data_62['预警等级'].drop_duplicates())
print(data_62['覆冰告警等级'].drop_duplicates())
print(data_99['预警等级'].drop_duplicates())
print(data_99['覆冰告警等级'].drop_duplicates())
```

```
0    正常
Name: 预警等级, dtype: object
0    0
Name: 覆冰告警等级, dtype: int64
1       橙色预警
2         正常
267     黄色预警
342     红色预警
Name: 预警等级, dtype: object
1      2
2      0
955    4
964    3
730    1
821    6
869    5
Name: 覆冰告警等级, dtype: int64
```

```
def warning_level_label_func(x):
  if x == '正常':
    return '0'
  elif x == '橙色预警':
    return '1'
  elif x == '黄色预警':
    return '2'
  elif x == '红色预警':
    return '3'
  else:
    print("预警等级错误")
    return

data_62['预警等级'] = data_62['预警等级'].map(warning_level_label_func)
data_62['预警等级'] = data_62['预警等级'].astype(int)
data_99['预警等级'] = data_99['预警等级'].map(warning_level_label_func)
data_99['预警等级'] = data_99['预警等级'].astype(int)
print(data_99['预警等级'].drop_duplicates())
```

```
1      1
2      0
267    2
342    3
Name: 预警等级, dtype: int64
```

```python
def monitor_label_func(x):
  if x == '62#':
    return 0
  elif x == '99#':
    return 1
  else:
    print("所属杆塔错误")
    return

data_62['所属杆塔'] = data_62['所属杆塔'].map(monitor_label_func)
data_99['所属杆塔'] = data_99['所属杆塔'].map(monitor_label_func)
data_99.dtypes
```

```
所属杆塔                 int64
测量时间        datetime64[ns]
气温                 float64
空气湿度               float64
风速                 float64
风向                 float64
气压                 float64
降雨量                float64
覆冰厚度               float64
覆冰占比               float64
拉力值                float64
辐射                 float64
覆冰告警等级               int64
预警等级                 int64
dtype: object
```

```python
data_99_sort_by_time = data_99.sort_values(by='测量时间')
print(data_99_sort_by_time['测量时间'])
print(data_99_sort_by_time)
```

```
1348   2022-12-01 02:04:02
1346   2022-12-01 03:06:02
1343   2022-12-01 04:05:02
1342   2022-12-01 04:06:01
1341   2022-12-01 05:04:02
               ...
9      2023-02-28 21:20:43
5      2023-02-28 22:05:04
4      2023-02-28 22:20:43
1      2023-02-28 23:05:03
0      2023-02-28 23:06:04
Name: 测量时间, Length: 2064, dtype: datetime64[ns]
      所属杆塔                测量时间    气温   空气湿度    风速     风向   气压  降雨
量  覆冰厚度  \
1348     1 2022-12-01 02:04:02 -2.27  93.00  0.73   31.0  0.0  0.0   0.0
1346     1 2022-12-01 03:06:02 -2.24  89.00  0.36   46.0  0.0  0.0   0.0
1343     1 2022-12-01 04:05:02 -1.21  89.00  0.30  182.0  0.0  0.0   0.0
1342     1 2022-12-01 04:06:01 -1.19  88.00  2.30  126.0  0.0  0.0   0.0
```

```
1341     1 2022-12-01 05:04:02 -1.19  88.00  2.30  126.0  0.0  0.0   0.0
...    ...                 ...   ...    ...   ...    ...  ...  ...   ...
9        1 2023-02-28 21:20:43  1.15  43.07  2.40  141.7  0.0  0.0   0.0
5        1 2023-02-28 22:05:04  2.83  34.00  0.31  237.0  0.0  0.0   0.0
4        1 2023-02-28 22:20:43  0.99  38.14  1.89  135.0  0.0  0.0   0.0
1        1 2023-02-28 23:05:03  2.83  34.00  0.31  237.0  0.0  0.0   0.0
0        1 2023-02-28 23:06:04  1.15  43.00  2.40  141.0  0.0  0.0   0.0

      覆冰占比  拉力值    辐射  覆冰告警等级  预警等级
1348   0.0  1.4   0.0       0     0
1346   0.0  1.9   0.0       0     0
1343   0.0  1.4   0.0       0     0
1342   0.0  1.9   0.0       0     0
1341   0.0  1.9   0.0       0     0
...    ...  ...   ...     ...   ...
9      0.0  1.9   0.0       0     0
5      0.0  1.4  24.0       0     0
4      0.0  1.9   0.0       0     0
1      0.0  1.4  24.0       0     0
0      0.0  1.9   0.0       0     0

[2064 rows x 14 columns]
```

exploratory data analysis

```
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib.pyplot import MultipleLocator # 设置刻度间隔
```

```
zh_to_en = {'气温': 'temp', '空气湿度': 'air_humidity', '风速': 'wind_speed', '风
向': 'wind_direction', \
            '气压': 'air_pressure', '降雨量': 'rainfall', '覆冰厚度':
'ice_thickness', '覆冰占比': 'percentage_of_ice_cover', \
            '拉力值': 'tension_value', '辐射': 'radiation'}
```

```
# features change with time
col_id = 2
plt.figure(figsize=(20, 20))
for subplot_id in range(1, 11):
  plt.subplot(5, 2, subplot_id)
  plt.plot(data_99_sort_by_time['测量时间'],
data_99_sort_by_time[data_99_sort_by_time.columns.tolist()[col_id]])
  plt.title(zh_to_en[data_99_sort_by_time.columns.tolist()[col_id]])
  col_id += 1
```

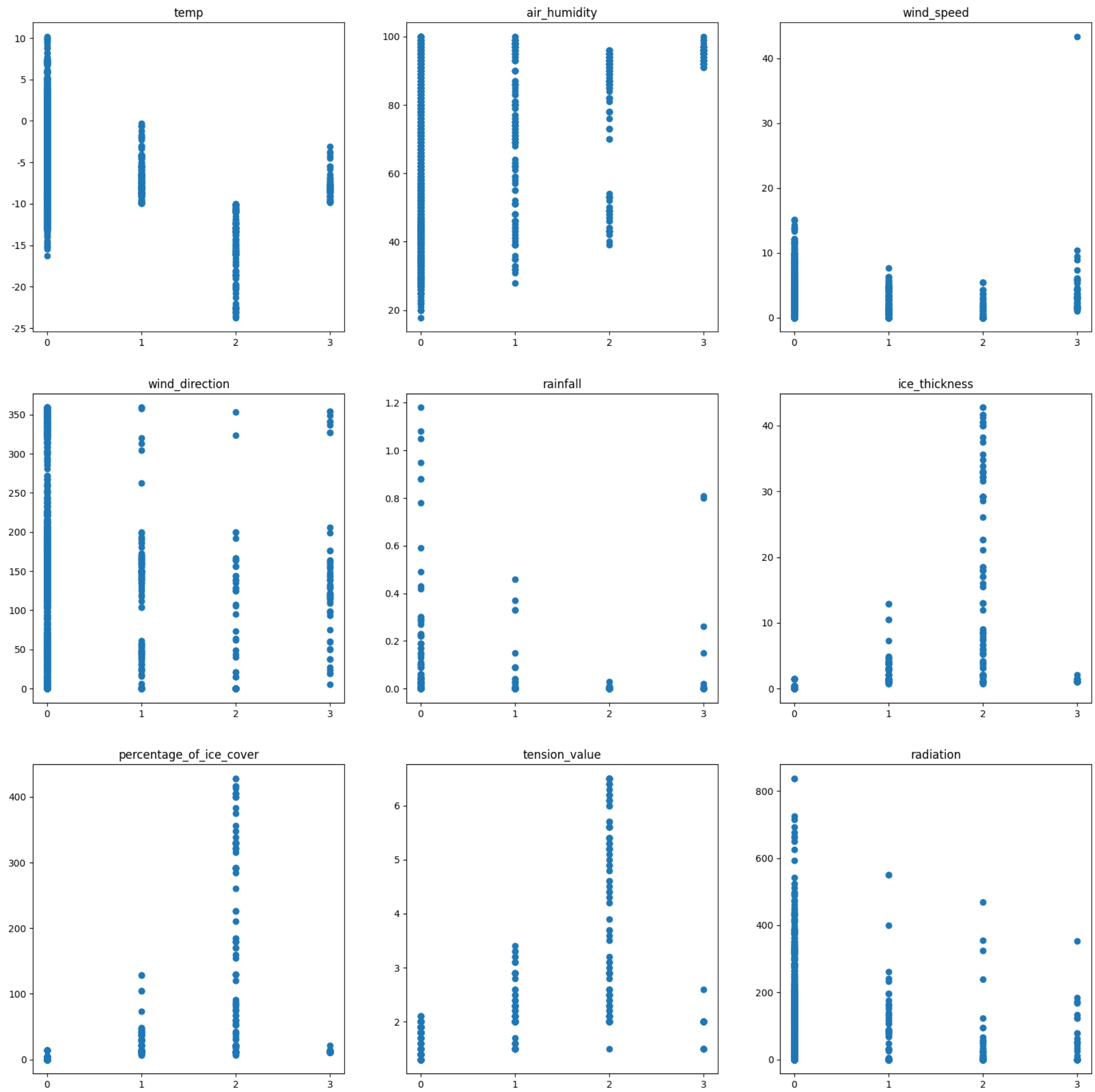

```
# delete air_pressure column by the above figure
delete_invalid_column(['气压'], data_99_sort_by_time)
data_99_sort_by_time.dtypes
```

```
所属杆塔                   int64
测量时间          datetime64[ns]
气温                   float64
空气湿度                 float64
风速                   float64
风向                   float64
降雨量                 float64
覆冰厚度                 float64
覆冰占比                 float64
拉力值                 float64
辐射                   float64
覆冰告警等级                 int64
预警等级                   int64
dtype: object
```

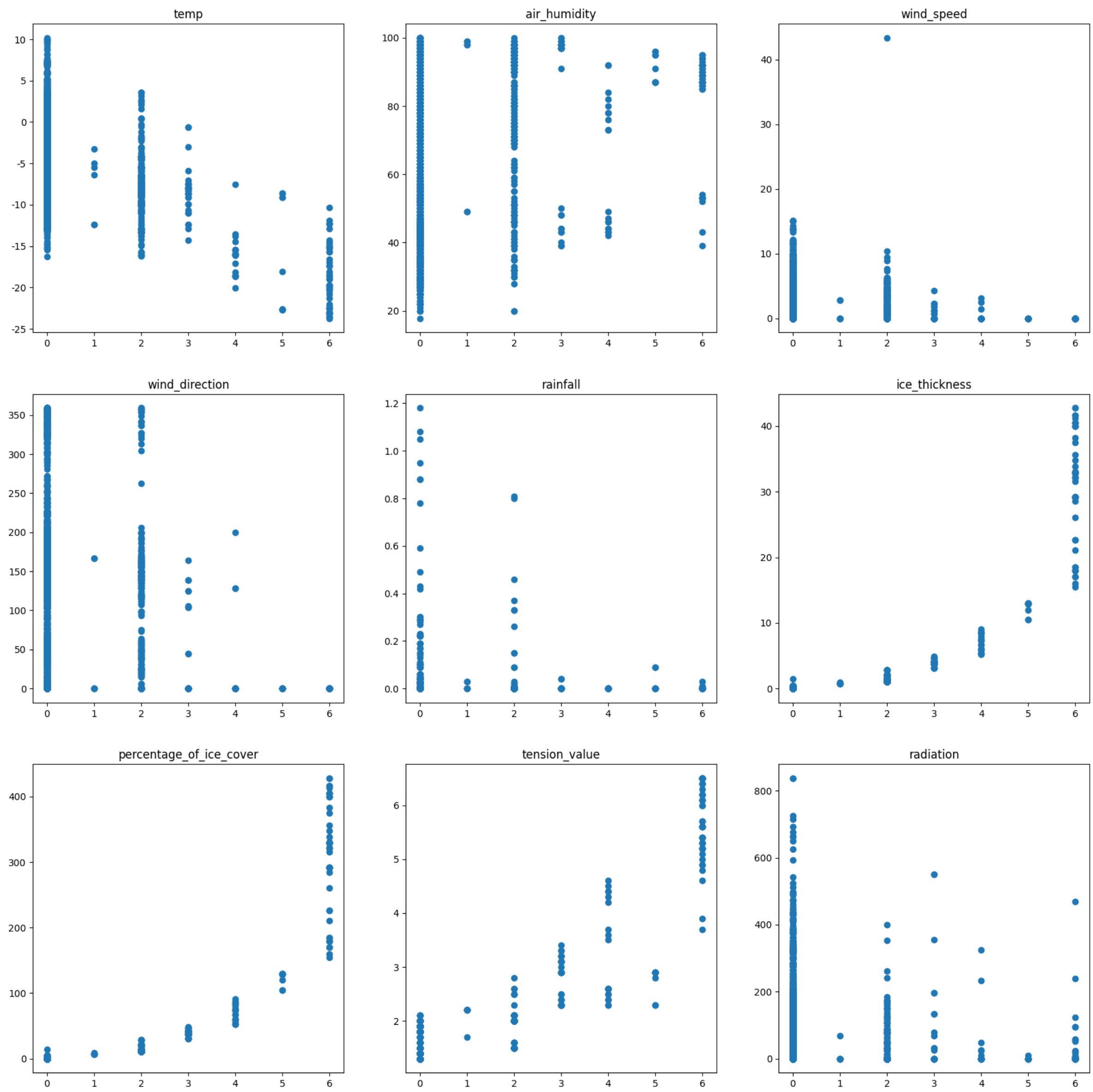
```
# impact of single feature on warning levels
col_id = 2
plt.figure(figsize=(20, 20))
for subplot_id in range(1, 10):
  plt.subplot(3, 3, subplot_id)
  plt.scatter(data_99_sort_by_time['预警等级'],
data_99_sort_by_time[data_99_sort_by_time.columns.tolist()[col_id]])
  plt.title(zh_to_en[data_99_sort_by_time.columns.tolist()[col_id]])

  # set the x-axis interval
  x_major_locator=MultipleLocator(1)
  ax=plt.gca()
  ax.xaxis.set_major_locator(x_major_locator)

  col_id += 1
```



```python
# impact of a single feature on ice cover alarm levels
col_id = 2
plt.figure(figsize=(20, 20))
for subplot_id in range(1, 10):
  plt.subplot(3, 3, subplot_id)
  plt.scatter(data_99_sort_by_time['覆冰告警等级'],
data_99_sort_by_time[data_99_sort_by_time.columns.tolist()[col_id]])
  plt.title(zh_to_en[data_99_sort_by_time.columns.tolist()[col_id]])
  col_id += 1
```

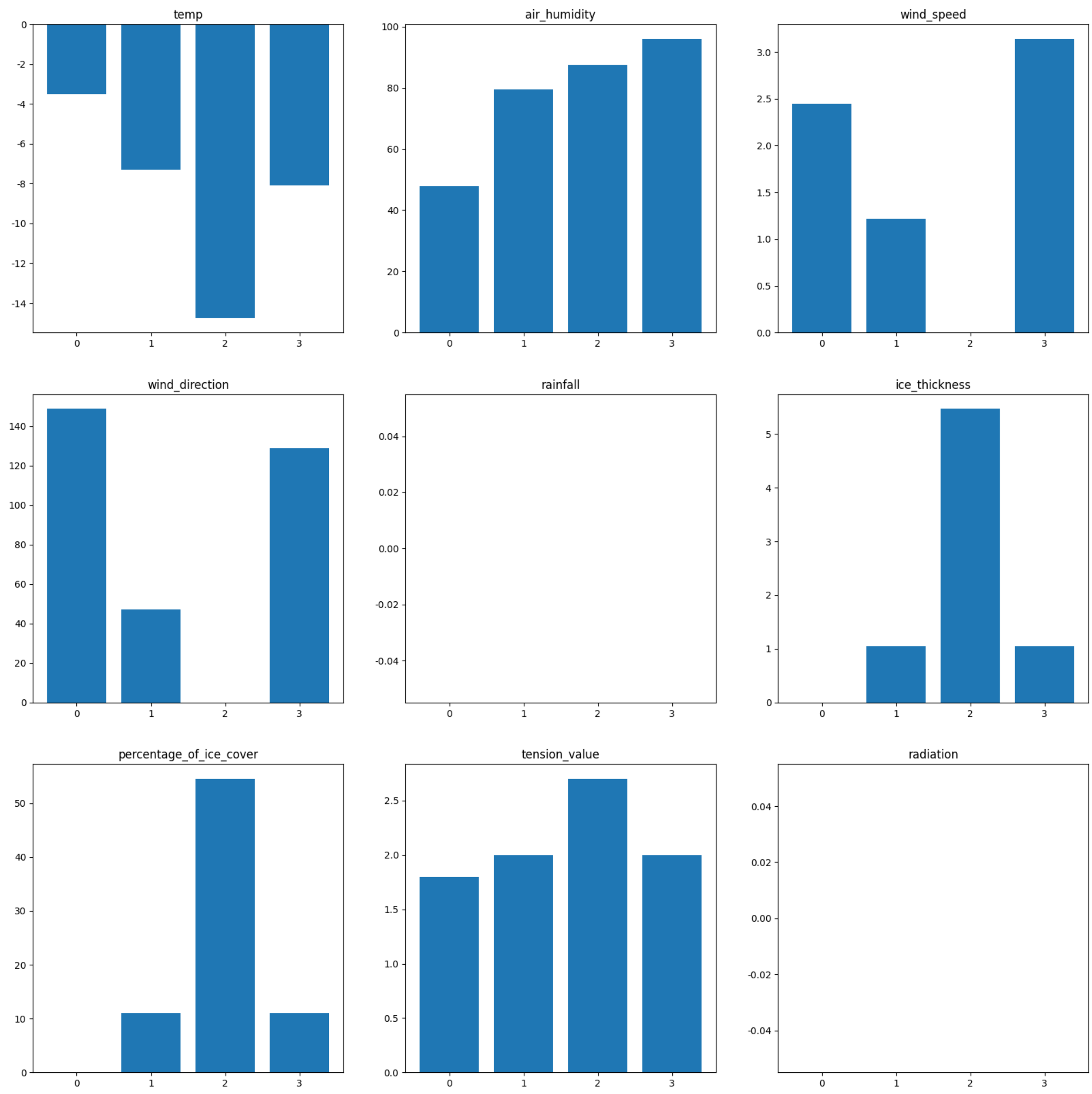



```python
# impact of single feature on warning levels
col_id = 2
plt.figure(figsize=(20, 20))
for subplot_id in range(1, 10):
  plt.subplot(3, 3, subplot_id)
  medians = []
  for warning_level in range(0, 4):
```

```
    medians.append(data_99_sort_by_time[data_99_sort_by_time['预警等级'] ==
warning_level][data_99_sort_by_time.columns.tolist()[col_id]].median())
  plt.bar(range(0, 4), medians)

  # set the x-axis interval
  x_major_locator=MultipleLocator(1)
  ax=plt.gca()
  ax.xaxis.set_major_locator(x_major_locator)

  plt.title(zh_to_en[data_99_sort_by_time.columns.tolist()[col_id]])
  col_id += 1
```

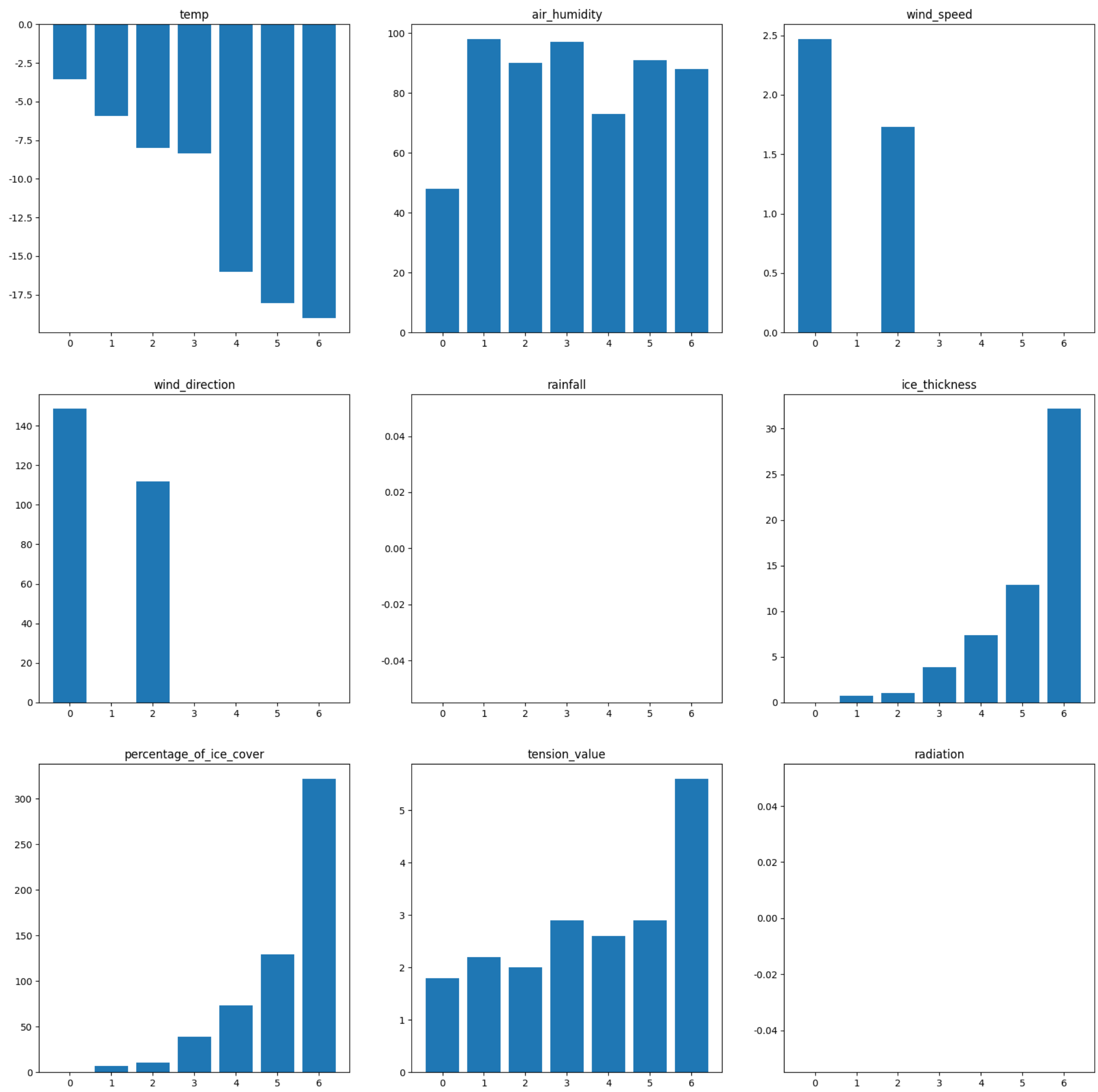



```
# impact of a single feature on ice cover alarm levels
col_id = 2
plt.figure(figsize=(20, 20))
for subplot_id in range(1, 10):
  plt.subplot(3, 3, subplot_id)
  medians = []
  for warning_level in range(0, 7):
```

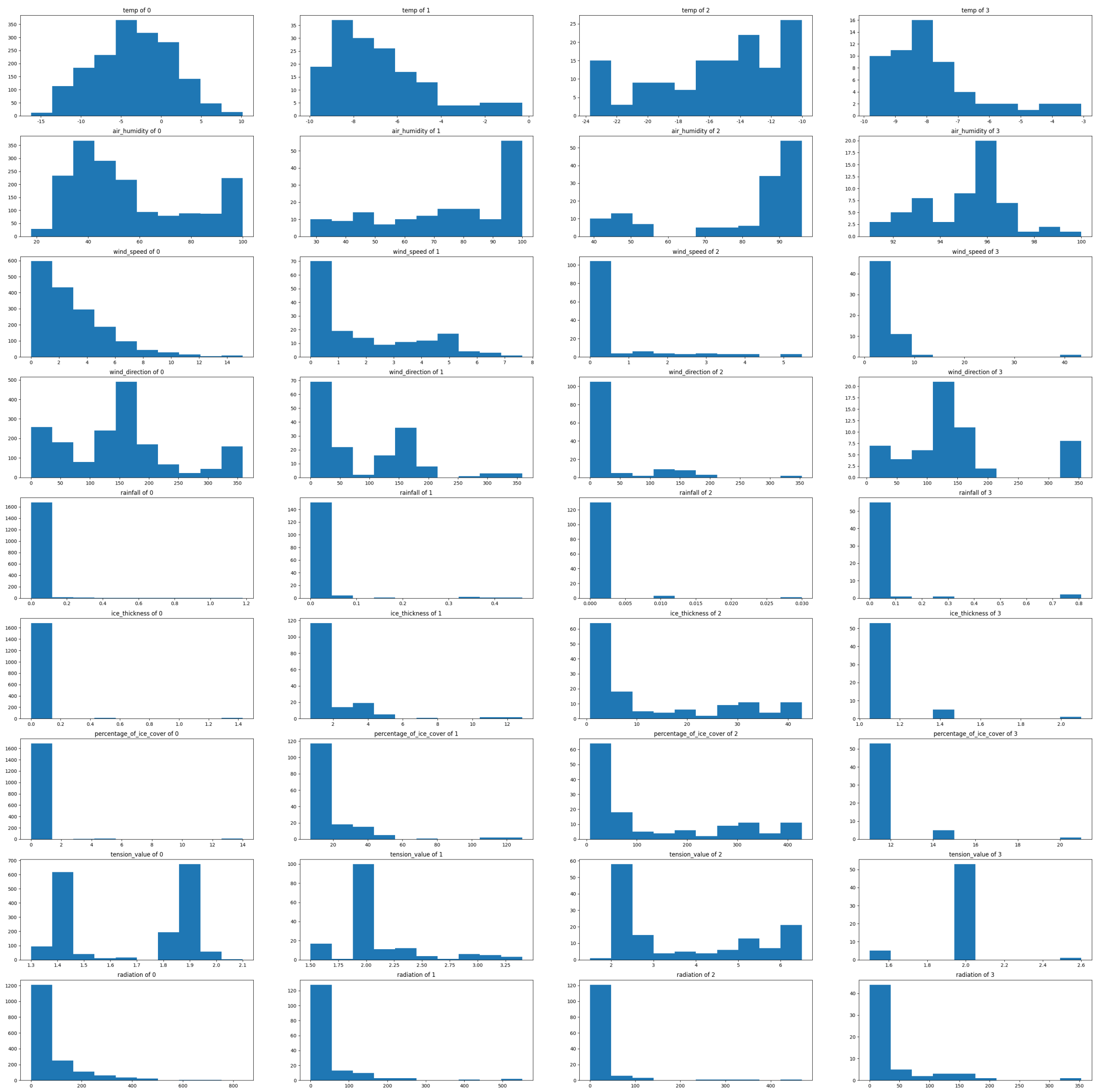
```
    medians.append(data_99_sort_by_time[data_99_sort_by_time['覆冰告警等级'] ==
warning_level][data_99_sort_by_time.columns.tolist()[col_id]].median())
  plt.bar(range(0, 7), medians)

  # set the x-axis interval
  x_major_locator=MultipleLocator(1)
  ax=plt.gca()
  ax.xaxis.set_major_locator(x_major_locator)

  plt.title(zh_to_en[data_99_sort_by_time.columns.tolist()[col_id]])
  col_id += 1
```



```
# distribution of features of different warning levels
col_id = 2
subplot_id = 1
plt.figure(figsize=(40, 40))
while subplot_id < 37:
  for warning_level in range(0, 4):
    plt.subplot(9, 4, subplot_id)
    plt.hist(data_99_sort_by_time[data_99_sort_by_time['预警等级'] ==
warning_level][data_99_sort_by_time.columns.tolist()[col_id]])
    plt.title(zh_to_en[data_99_sort_by_time.columns.tolist()[col_id]]+" of
"+str(warning_level))
    subplot_id += 1
  col_id += 1
```



```
# distribution of features of different ice cover alarm levels
col_id = 2
subplot_id = 1
plt.figure(figsize=(80, 80))
while subplot_id < 64:
  for warning_level in range(0, 7):
    plt.subplot(9, 7, subplot_id)
    plt.hist(data_99_sort_by_time[data_99_sort_by_time['覆冰告警等级'] ==
warning_level][data_99_sort_by_time.columns.tolist()[col_id]])
    plt.title(zh_to_en[data_99_sort_by_time.columns.tolist()[col_id]]+" of
"+str(warning_level))
    subplot_id += 1
  col_id += 1
```

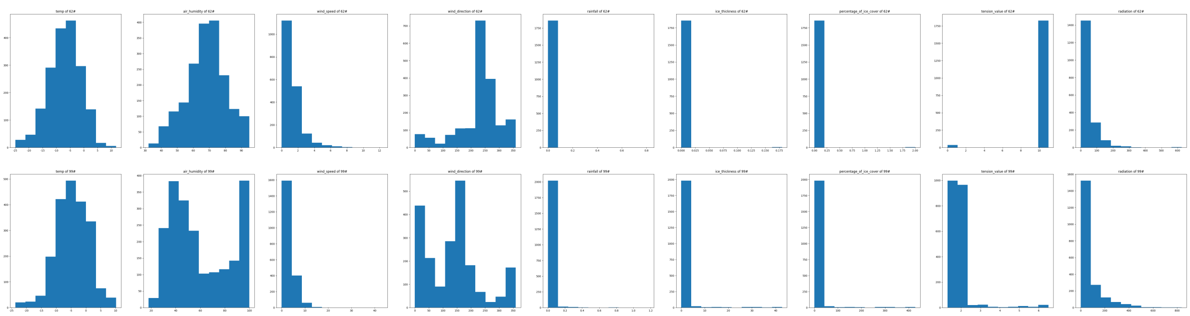
```
delete_invalid_column(['气压'], data_62)
data_62.dtypes
```

```
所属杆塔              int64
测量时间        datetime64[ns]
气温                float64
空气湿度              float64
风速                float64
风向                float64
降雨量               float64
覆冰厚度              float64
覆冰占比              float64
拉力值               float64
辐射                float64
覆冰告警等级              int64
预警等级              int64
dtype: object
```

```
# distribution of features of different monitoring sites
plt.figure(figsize=(80, 20))

col_id = 2
for subplot_id in range(1, 10):
  plt.subplot(2, 9, subplot_id)
  plt.hist(data_62[data_62.columns.tolist()[col_id]])
  plt.title(zh_to_en[data_62.columns.tolist()[col_id]]+" of 62#")
  col_id += 1

col_id = 2
for subplot_id in range(10, 19):
  plt.subplot(2, 9, subplot_id)
  plt.hist(data_99_sort_by_time[data_99_sort_by_time.columns.tolist()[col_id]])
  plt.title(zh_to_en[data_99_sort_by_time.columns.tolist()[col_id]]+" of 99#")
  col_id += 1
```



modeling & evaluation

研究问题

1. 分类

- 通过气象数据分类监测位
- 通过气象数据预测覆冰告警等级

2. 聚类

- 聚类天气类型

```
import lightgbm as lgb
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report
```

```
# classify monitoring sites (all features)
data_all = pd.concat([data_62, data_99_sort_by_time], axis=0)
x = data_all.iloc[:, 2:11]
y = data_all['所属杆塔']

scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)

x_train, x_test, y_train, y_test = train_test_split(x_scaled, y, test_size=0.2,
random_state=42)
```

```
# train lgbm model
train_data = lgb.Dataset(x_train, label=y_train)
test_data = lgb.Dataset(x_test, label=y_test, reference=train_data)

params = {
    'objective': 'multiclass',
    'num_class': 2,
    'metric': 'multi_logloss',
    'boosting_type': 'gbdt',
    'learning_rate': 0.1,
    'num_leaves': 31,
    'feature_fraction': 0.9
}

num_round = 100
bst = lgb.train(params, train_data, num_round, valid_sets=[test_data])
```

```
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing
was 0.193412 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 1291
[LightGBM] [Info] Number of data points in the train set: 3142, number of used
features: 9
[LightGBM] [Info] Start training from score -0.766423
[LightGBM] [Info] Start training from score -0.624876
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
```

```
# prediction & evaluation
y_pred_prob = bst.predict(x_test, num_iteration=bst.best_iteration)
y_pred = [list(x).index(max(x)) for x in y_pred_prob]
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       404
           1       1.00      1.00      1.00       382

    accuracy                           1.00       786
   macro avg       1.00      1.00      1.00       786
weighted avg       1.00      1.00      1.00       786
```

```
# train svm model
svm_model = SVC(kernel='rbf', C=1.0)

svm_model.fit(x_train, y_train)
```

```
# prediction & evaluation
y_pred = svm_model.predict(x_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      0.98      0.99       404
           1       0.97      1.00      0.99       382

    accuracy                           0.99       786
   macro avg       0.99      0.99      0.99       786
weighted avg       0.99      0.99      0.99       786
```

```
# classify monitoring sites (choose features by EDA)
x = data_all.iloc[:, [3, 5, 9]]
y = data_all['所属杆塔']

scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,
random_state=42)
```

```
# train lgbm model
train_data = lgb.Dataset(x_train, label=y_train)
test_data = lgb.Dataset(x_test, label=y_test, reference=train_data)

params = {
```

```
    'objective': 'multiclass',
    'num_class': 2,
    'metric': 'multi_logloss',
    'boosting_type': 'gbdt',
    'learning_rate': 0.1,
    'num_leaves': 31,
    'feature_fraction': 0.9
}

num_round = 100
bst = lgb.train(params, train_data, num_round, valid_sets=[test_data])
```

```
# prediction & evaluation
y_pred_prob = bst.predict(x_test, num_iteration=bst.best_iteration)
y_pred = [list(x).index(max(x)) for x in y_pred_prob]
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       404
           1       1.00      1.00      1.00       382

    accuracy                           1.00       786
   macro avg       1.00      1.00      1.00       786
weighted avg       1.00      1.00      1.00       786
```

```
# train svm model
svm_model = SVC(kernel='rbf', C=1.0)

svm_model.fit(x_train, y_train)
```

```
# predict & evaluation
y_pred = svm_model.predict(x_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      0.97      0.98       404
           1       0.97      1.00      0.98       382

    accuracy                           0.98       786
   macro avg       0.98      0.98      0.98       786
weighted avg       0.98      0.98      0.98       786
```

```
import tensorflow as tf
from sklearn.ensemble import RandomForestClassifier
```

```
# classify warning level (all features)
x = data_all.iloc[:, 2:11]
y = data_all['覆冰告警等级']

scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)

x_train, x_test, y_train, y_test = train_test_split(x_scaled, y, test_size=0.2,
random_state=42)
```

```
# build DNN and train
model = tf.keras.Sequential([
    tf.keras.layers.Dense(64, activation='relu', input_shape=
(x_train.shape[1],)),
    tf.keras.layers.Dense(32, activation='relu'),
    tf.keras.layers.Dense(7, activation='softmax')
])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(x_train, y_train, epochs=50, batch_size=32, validation_data=(x_test,
y_test))
```

```
Epoch 1/50
99/99 [==============================] - 1s 4ms/step - loss: 0.8943 - accuracy:
0.8135 - val_loss: 0.3441 - val_accuracy: 0.9059
Epoch 2/50
99/99 [==============================] - 0s 3ms/step - loss: 0.2304 - accuracy:
0.9255 - val_loss: 0.2201 - val_accuracy: 0.9097
Epoch 3/50
99/99 [==============================] - 0s 3ms/step - loss: 0.1594 - accuracy:
0.9440 - val_loss: 0.1620 - val_accuracy: 0.9440
Epoch 4/50
99/99 [==============================] - 0s 3ms/step - loss: 0.1152 - accuracy:
0.9634 - val_loss: 0.1132 - val_accuracy: 0.9656
Epoch 5/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0815 - accuracy:
0.9736 - val_loss: 0.0865 - val_accuracy: 0.9707
Epoch 6/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0599 - accuracy:
0.9822 - val_loss: 0.0683 - val_accuracy: 0.9758
Epoch 7/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0467 - accuracy:
0.9857 - val_loss: 0.0538 - val_accuracy: 0.9809
Epoch 8/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0391 - accuracy:
0.9876 - val_loss: 0.0464 - val_accuracy: 0.9924
Epoch 9/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0336 - accuracy:
0.9911 - val_loss: 0.0402 - val_accuracy: 0.9898
Epoch 10/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0294 - accuracy:
0.9927 - val_loss: 0.0345 - val_accuracy: 0.9924
Epoch 11/50
```

```
99/99 [==============================] - 0s 3ms/step - loss: 0.0259 - accuracy: 0.9924 - val_loss: 0.0312 - val_accuracy: 0.9924
Epoch 12/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0240 - accuracy: 0.9943 - val_loss: 0.0267 - val_accuracy: 0.9949
Epoch 13/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0216 - accuracy: 0.9946 - val_loss: 0.0251 - val_accuracy: 0.9949
Epoch 14/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0190 - accuracy: 0.9955 - val_loss: 0.0229 - val_accuracy: 0.9975
Epoch 15/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0172 - accuracy: 0.9955 - val_loss: 0.0210 - val_accuracy: 0.9975
Epoch 16/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0154 - accuracy: 0.9968 - val_loss: 0.0186 - val_accuracy: 0.9975
Epoch 17/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0142 - accuracy: 0.9971 - val_loss: 0.0148 - val_accuracy: 0.9987
Epoch 18/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0127 - accuracy: 0.9975 - val_loss: 0.0151 - val_accuracy: 0.9987
Epoch 19/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0116 - accuracy: 0.9968 - val_loss: 0.0128 - val_accuracy: 0.9987
Epoch 20/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0105 - accuracy: 0.9978 - val_loss: 0.0132 - val_accuracy: 0.9987
Epoch 21/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0097 - accuracy: 0.9987 - val_loss: 0.0106 - val_accuracy: 0.9987
Epoch 22/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0090 - accuracy: 0.9984 - val_loss: 0.0098 - val_accuracy: 0.9987
Epoch 23/50
99/99 [==============================] - 0s 4ms/step - loss: 0.0080 - accuracy: 0.9984 - val_loss: 0.0091 - val_accuracy: 0.9987
Epoch 24/50
99/99 [==============================] - 0s 4ms/step - loss: 0.0073 - accuracy: 0.9990 - val_loss: 0.0090 - val_accuracy: 0.9987
Epoch 25/50
99/99 [==============================] - 0s 5ms/step - loss: 0.0068 - accuracy: 0.9994 - val_loss: 0.0086 - val_accuracy: 0.9987
Epoch 26/50
99/99 [==============================] - 0s 4ms/step - loss: 0.0063 - accuracy: 0.9994 - val_loss: 0.0080 - val_accuracy: 0.9987
Epoch 27/50
99/99 [==============================] - 0s 5ms/step - loss: 0.0059 - accuracy: 0.9994 - val_loss: 0.0076 - val_accuracy: 0.9987
Epoch 28/50
99/99 [==============================] - 0s 5ms/step - loss: 0.0054 - accuracy: 0.9990 - val_loss: 0.0090 - val_accuracy: 0.9987
Epoch 29/50
99/99 [==============================] - 0s 5ms/step - loss: 0.0051 - accuracy: 0.9994 - val_loss: 0.0062 - val_accuracy: 0.9987
Epoch 30/50
```

```
99/99 [==============================] - 0s 4ms/step - loss: 0.0048 - accuracy:
0.9994 - val_loss: 0.0067 - val_accuracy: 0.9987
Epoch 31/50
99/99 [==============================] - 0s 4ms/step - loss: 0.0040 - accuracy:
1.0000 - val_loss: 0.0050 - val_accuracy: 1.0000
Epoch 32/50
99/99 [==============================] - 0s 5ms/step - loss: 0.0042 - accuracy:
0.9990 - val_loss: 0.0080 - val_accuracy: 0.9987
Epoch 33/50
99/99 [==============================] - 0s 5ms/step - loss: 0.0038 - accuracy:
0.9997 - val_loss: 0.0076 - val_accuracy: 0.9987
Epoch 34/50
99/99 [==============================] - 0s 5ms/step - loss: 0.0036 - accuracy:
0.9994 - val_loss: 0.0089 - val_accuracy: 0.9987
Epoch 35/50
99/99 [==============================] - 0s 4ms/step - loss: 0.0036 - accuracy:
0.9994 - val_loss: 0.0094 - val_accuracy: 0.9987
Epoch 36/50
99/99 [==============================] - 1s 5ms/step - loss: 0.0043 - accuracy:
0.9990 - val_loss: 0.0134 - val_accuracy: 0.9987
Epoch 37/50
99/99 [==============================] - 0s 4ms/step - loss: 0.0047 - accuracy:
0.9987 - val_loss: 0.0086 - val_accuracy: 0.9987
Epoch 38/50
99/99 [==============================] - 0s 5ms/step - loss: 0.0029 - accuracy:
0.9997 - val_loss: 0.0075 - val_accuracy: 0.9987
Epoch 39/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0025 - accuracy:
0.9997 - val_loss: 0.0065 - val_accuracy: 0.9987
Epoch 40/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0024 - accuracy:
1.0000 - val_loss: 0.0120 - val_accuracy: 0.9987
Epoch 41/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0023 - accuracy:
0.9997 - val_loss: 0.0080 - val_accuracy: 0.9987
Epoch 42/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0028 - accuracy:
0.9990 - val_loss: 0.0075 - val_accuracy: 0.9987
Epoch 43/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0023 - accuracy:
0.9997 - val_loss: 0.0095 - val_accuracy: 0.9987
Epoch 44/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0018 - accuracy:
1.0000 - val_loss: 0.0158 - val_accuracy: 0.9987
Epoch 45/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0022 - accuracy:
0.9997 - val_loss: 0.0122 - val_accuracy: 0.9987
Epoch 46/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0019 - accuracy:
1.0000 - val_loss: 0.0151 - val_accuracy: 0.9987
Epoch 47/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0016 - accuracy:
1.0000 - val_loss: 0.0148 - val_accuracy: 0.9987
Epoch 48/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0017 - accuracy:
1.0000 - val_loss: 0.0137 - val_accuracy: 0.9987
Epoch 49/50
```

```
99/99 [==============================] - 0s 3ms/step - loss: 0.0016 - accuracy:
1.0000 - val_loss: 0.0154 - val_accuracy: 0.9987
Epoch 50/50
99/99 [==============================] - 0s 3ms/step - loss: 0.0016 - accuracy:
1.0000 - val_loss: 0.0172 - val_accuracy: 0.9987
```

```
<keras.src.callbacks.History at 0x7e1cd25f25c0>
```

```
# prediction & evaluation
y_pred_prob = model.predict(x_test)
y_pred = [tf.argmax(x).numpy() for x in y_pred_prob]
print(classification_report(y_test, y_pred))
```

```
25/25 [==============================] - 0s 2ms/step
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       706
           2       1.00      0.98      0.99        56
           3       1.00      1.00      1.00        11
           4       1.00      1.00      1.00         5
           5       1.00      1.00      1.00         2
           6       1.00      1.00      1.00         6

    accuracy                           1.00       786
   macro avg       1.00      1.00      1.00       786
weighted avg       1.00      1.00      1.00       786
```

```
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(x_train, y_train)
```

```
y_pred = rf_model.predict(x_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       706
           2       1.00      1.00      1.00        56
           3       1.00      1.00      1.00        11
           4       1.00      1.00      1.00         5
           5       1.00      1.00      1.00         2
           6       1.00      1.00      1.00         6

    accuracy                           1.00       786
   macro avg       1.00      1.00      1.00       786
weighted avg       1.00      1.00      1.00       786
```

```python
from sklearn.cluster import KMeans, AgglomerativeClustering
from sklearn.metrics import silhouette_score, davies_bouldin_score,
calinski_harabasz_score
```

```python
# cluster data
scaler = StandardScaler()
data_scaled = scaler.fit_transform(data_all.iloc[:, 2:11])

# sunny cloudy rainy
kmeans = KMeans(n_clusters=3, random_state=42)
kmeans.fit(data_scaled)
```

```python
labels = kmeans.labels_

np.set_printoptions(threshold=np.inf)
print(labels)
```

```
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 0 0 0 0 0 0]
```

```python
silhouette_avg = silhouette_score(data_scaled, labels) # -1 ~ 1; the closer to 1, the better
print(silhouette_avg)
calinski_harabasz_score_value = calinski_harabasz_score(data_scaled, labels)
print(calinski_harabasz_score_value)
davies_bouldin_score_value = davies_bouldin_score(data_scaled, labels)
print(davies_bouldin_score_value)
```

```
0.2747482239500282
1177.2740587984551
1.1909673990978027
```

```python
agg_clustering = AgglomerativeClustering(n_clusters=3)
agg_labels = agg_clustering.fit_predict(data_scaled)

np.set_printoptions(threshold=np.inf)
print(agg_labels)
```

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silhouette_avg = silhouette_score(data_scaled, agg_labels) # -1 ~ 1; the closer
to 1, the better
print(silhouette_avg)
calinski_harabasz_score_value = calinski_harabasz_score(data_scaled, agg_labels)
# the bigger, the better
print(calinski_harabasz_score_value)
davies_bouldin_score_value = davies_bouldin_score(data_scaled, agg_labels) # the
smaller, the better
print(davies_bouldin_score_value)
```

```
0.2675286000392134
1103.971276552673
1.1639099327461782
```

```
def unify_label(x):
  if x == 1:
    return 2
  elif x == 2:
    return 1
  else:
    return 0

for i in range(0, len(labels)):
  labels[i] = unify_label(labels[i])
```

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print(labels != agg_labels)
```

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