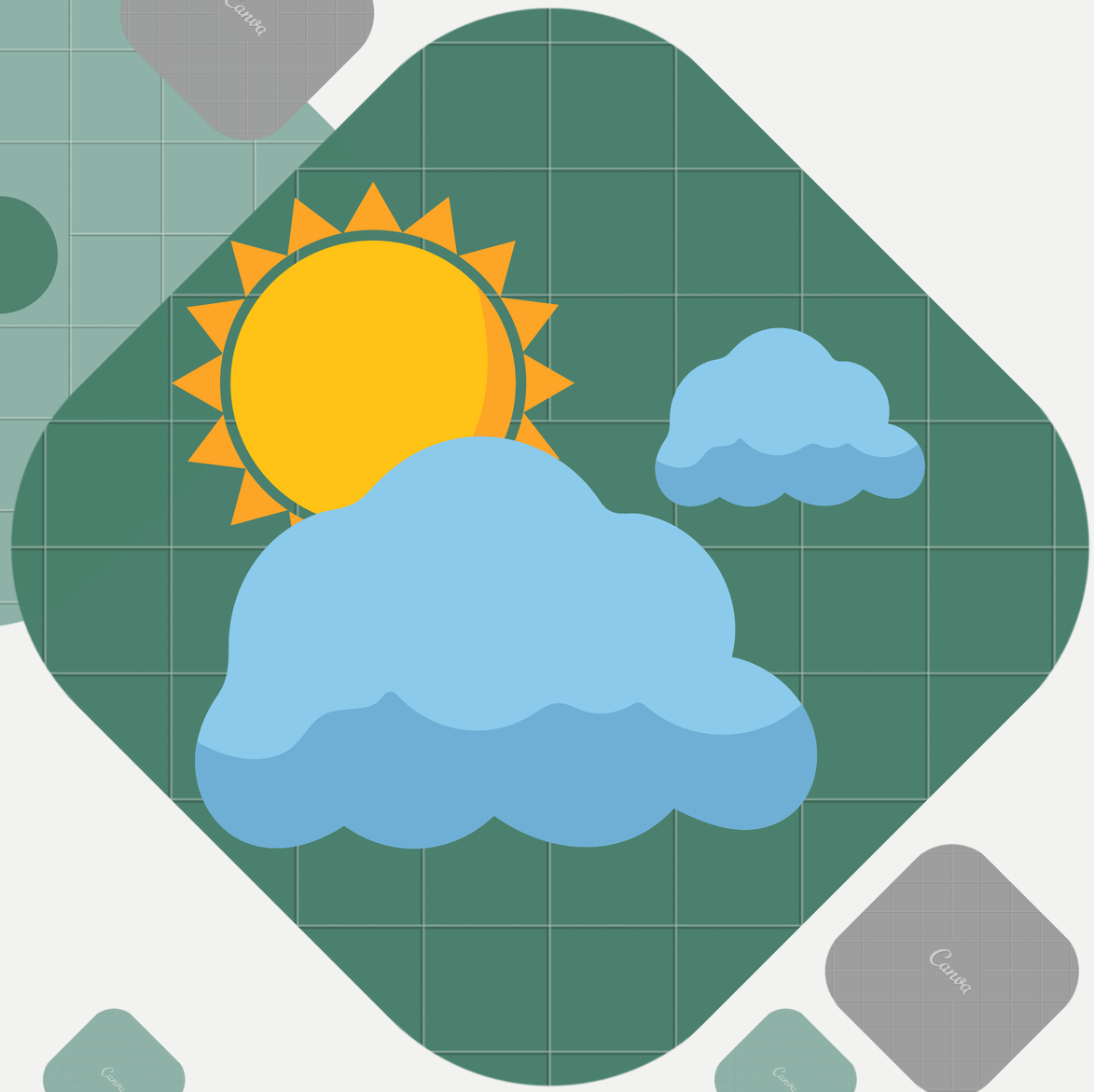


WEATHERSENSE PROJECT

WEATHER SENSE

Presentation, April 2024

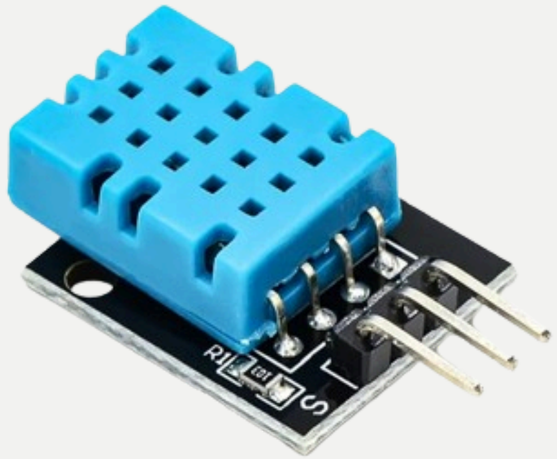
PRESENTATION

About Project

WeatherSense is a weather tracking website that updates weather data and classification every 10 minutes. Leveraging our trained random forest classification model, WeatherSense provides accurate classification and historical weather information.

PRIMANRY DATA

OUR PRIMARY DATA IS COLLECTED BY THE KIDBRIGHT BOARD, INCORPORATING A TEMPERATURE AND HUMIDITY SENSOR FROM THE KY-015 MODULE, AND USING MQTT TO SEND A DATA TO NODERED



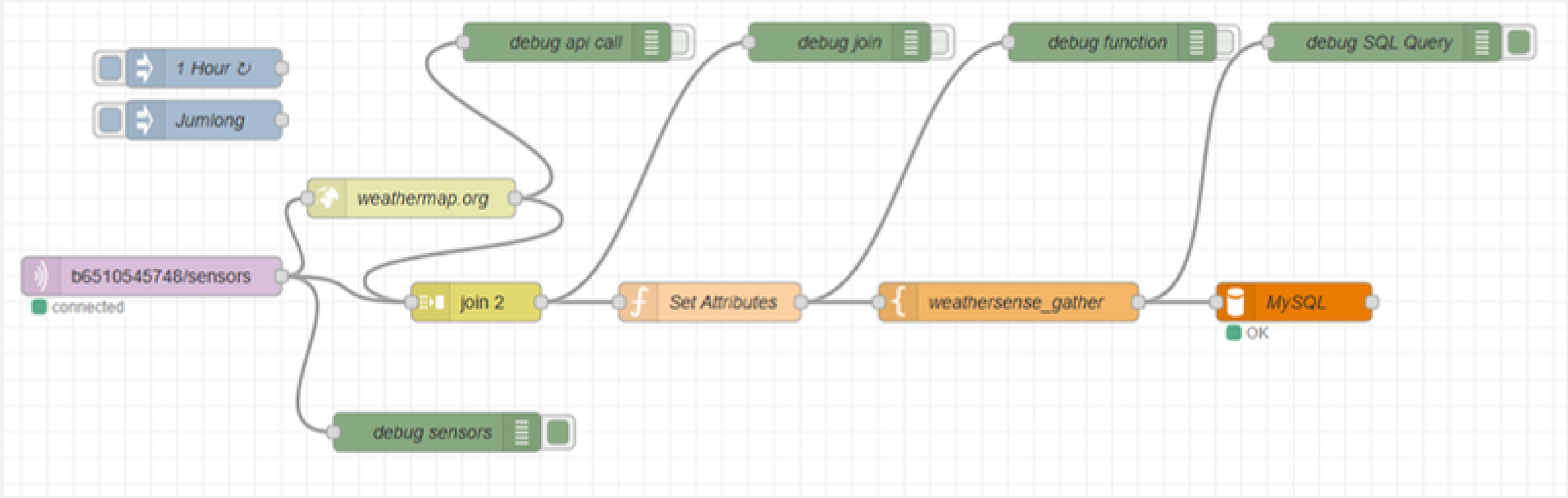
SECONDARY DATA

OUR SECONDARY DATA IS COLLECTED BY CALL API FROM OPENWEATHERMAP API (CURRENT WEATHER) USING NODERED TO FETCH DATA FROM API

ATTRIBUTE SELECT:

- **HUMIDITY (%)**
- **TEMPERATURE (DEGREE CELSIUS)**
- **PRESSURE (HPA)**
- **CLOUDINESS (%)**
- **WEATHER: SUCH AS CLOUD, FEW CLOUDS ETC.**

NODE RED IMPLEMENTATION



DATA EXPLORLATION

USING PYTHON PANDAS TO EXPLORE AND PREPROCESSING MORE OVER TRAINING A MODEL.

DATA EXPLORATION

CHECKING DATA TYPE OF DATAFRAME

```
id                 int64
ts                object
temp_sensor        int64
humidity_sensor    int64
temp_api         float64
humidity_api       int64
pressure           int64
wind_speed       float64
cloudiness         int64
weather           object
dtype: object
```

DATA EXPLORATION

CHANGE TYPE OF TS TO DATETIME TYPE

```
1  data['ts'] = pd.to_datetime(data['ts'])
2  display(data.head())
```

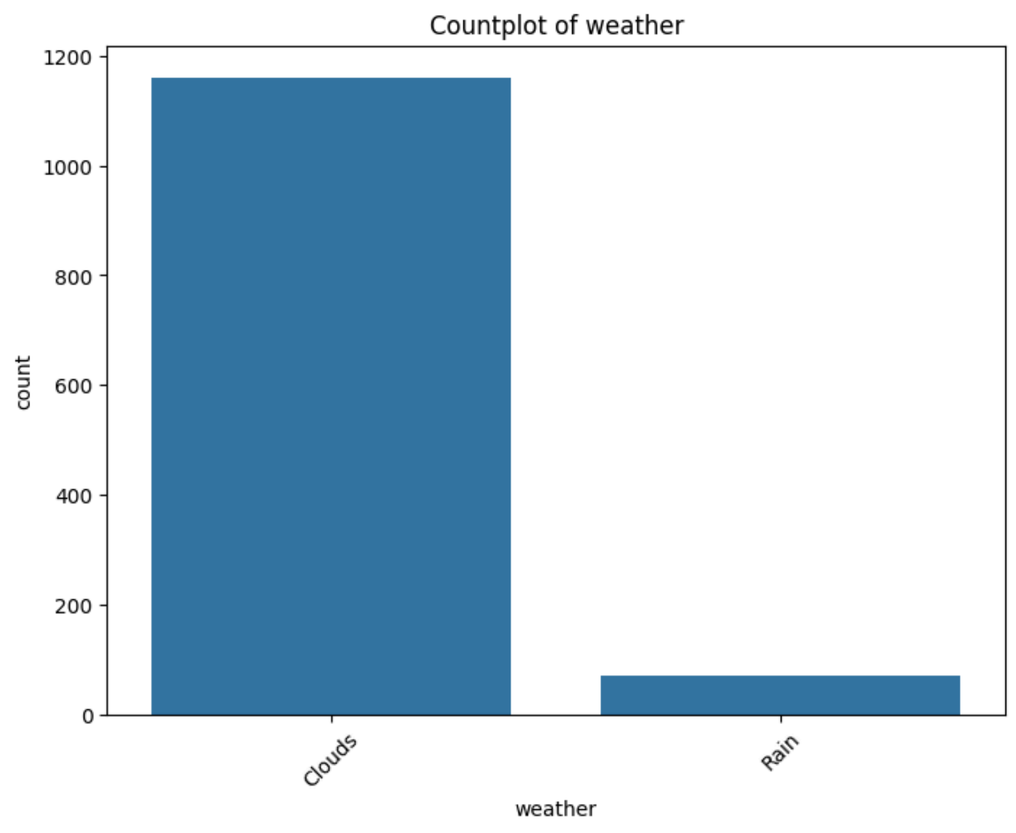
DATA EXPLORATION

- **RETRIEVE A SUMMARY STATISTIC OF THIS DATASET.**

	id	ts	temp_sensor	humidity_sensor	temp_api	humidity_api	pressure	wind_speed	cloudiness
count	1232.000000	1232	1232.000000	1232.000000	1232.000000	1232.000000	1232.000000	1232.000000	1232.000000
mean	616.500000	2024-04-28 05:42:56.026785792	33.039773	71.299513	33.911964	64.646916	1005.815747	4.595649	21.363636
min	1.000000	2024-04-21 17:34:59	22.000000	26.000000	28.860000	26.000000	1000.000000	1.030000	20.000000
25%	308.750000	2024-04-24 20:33:47.750000128	33.000000	68.000000	31.130000	52.000000	1005.000000	3.600000	20.000000
50%	616.500000	2024-04-27 14:51:34	33.000000	73.000000	32.690000	70.000000	1006.000000	4.630000	20.000000
75%	924.250000	2024-05-01 18:49:37.500000	34.000000	77.000000	37.190000	78.000000	1007.000000	5.140000	20.000000
max	1232.000000	2024-05-07 02:21:56	35.000000	95.000000	41.220000	90.000000	1010.000000	8.230000	40.000000
std	355.792074	NaN	1.904941	7.383676	3.152121	15.168092	1.842096	1.232721	5.043200

DATA EXPLORATION

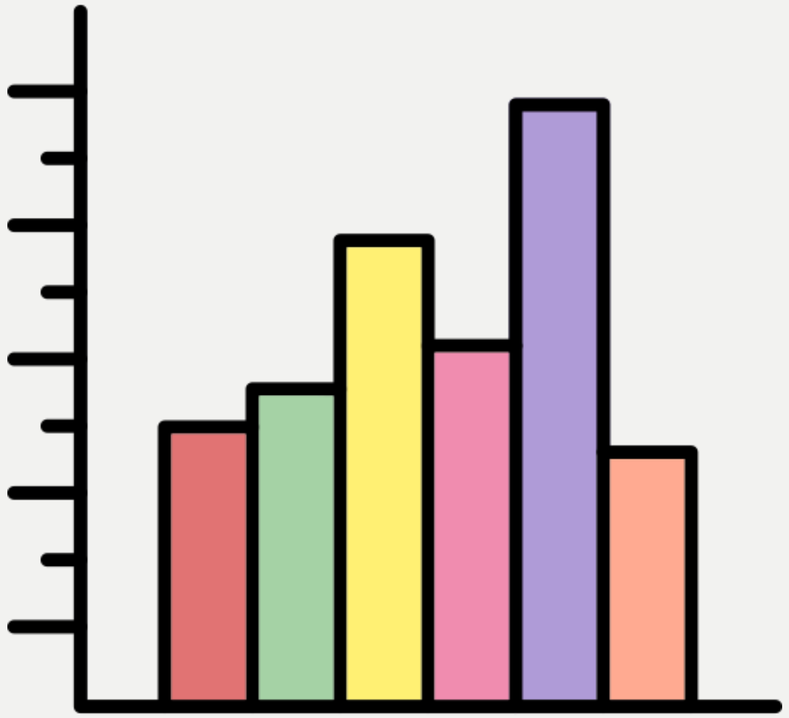
- FOR CATEGORICAL FEATURES USING COUNT PLOTS.

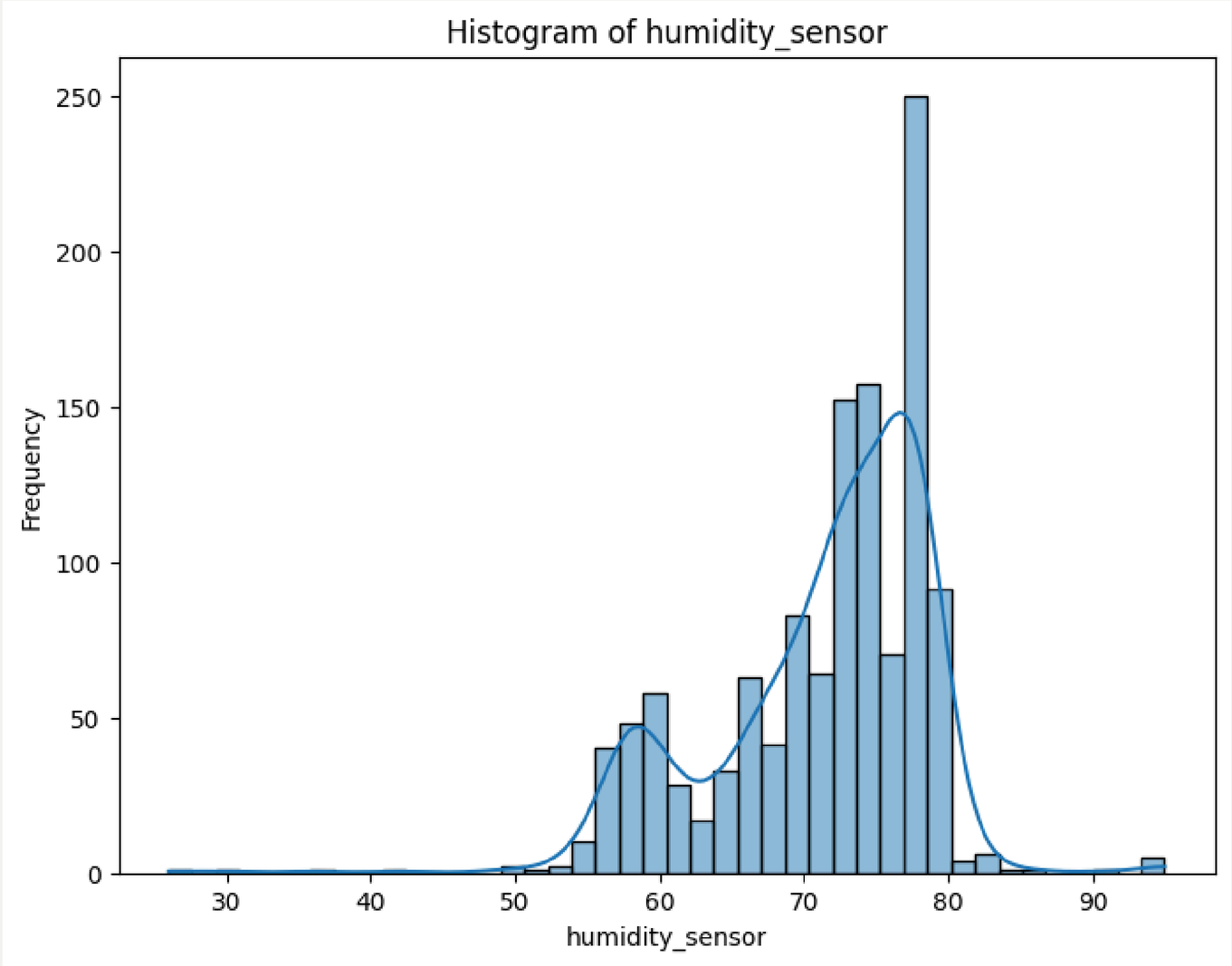


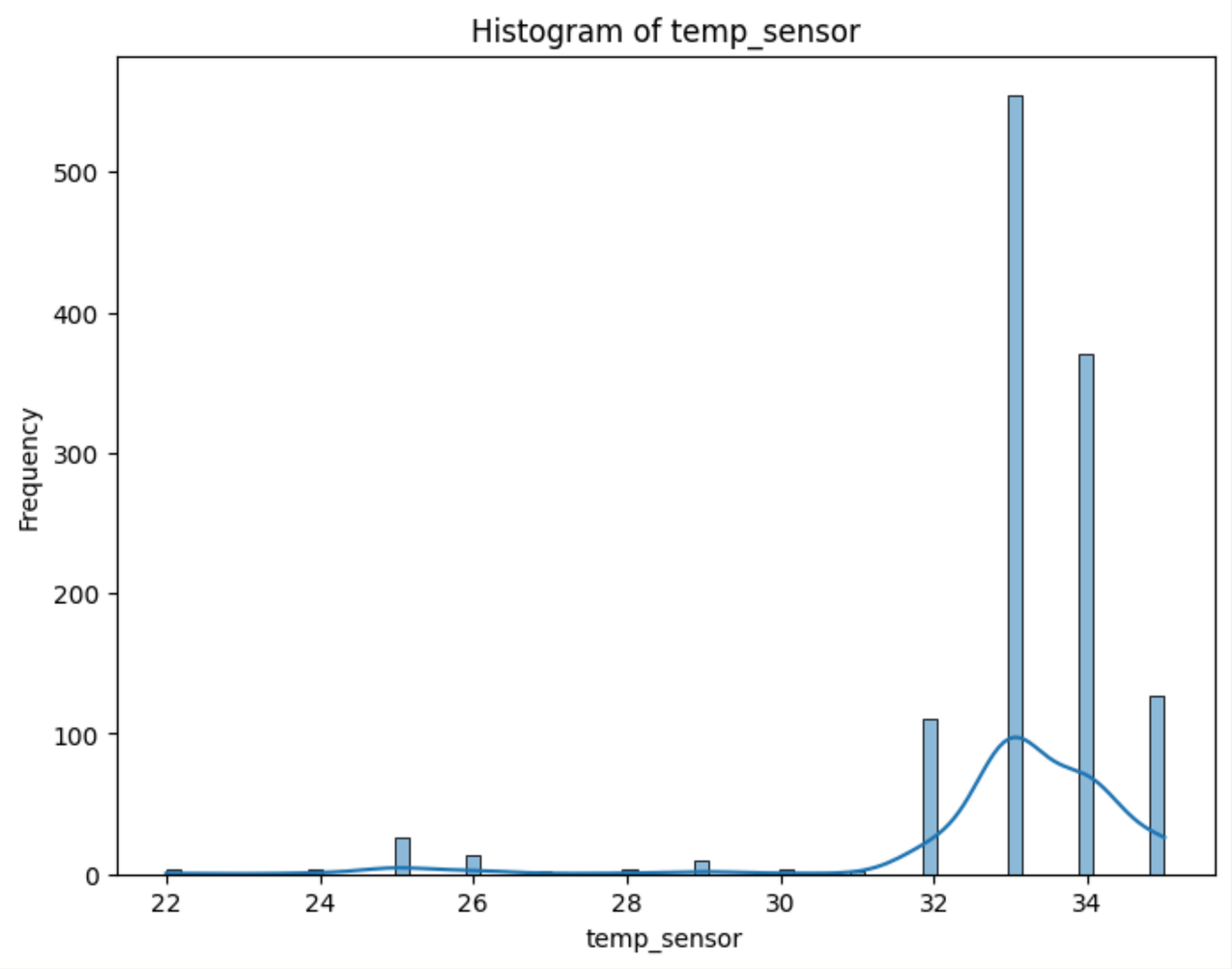
From the histogram plot, it's evident that the data clouds contain a large number of values, whereas instances of rain are scarce. This imbalance can lead to a data problem, which we need to address during the preprocessing stage.

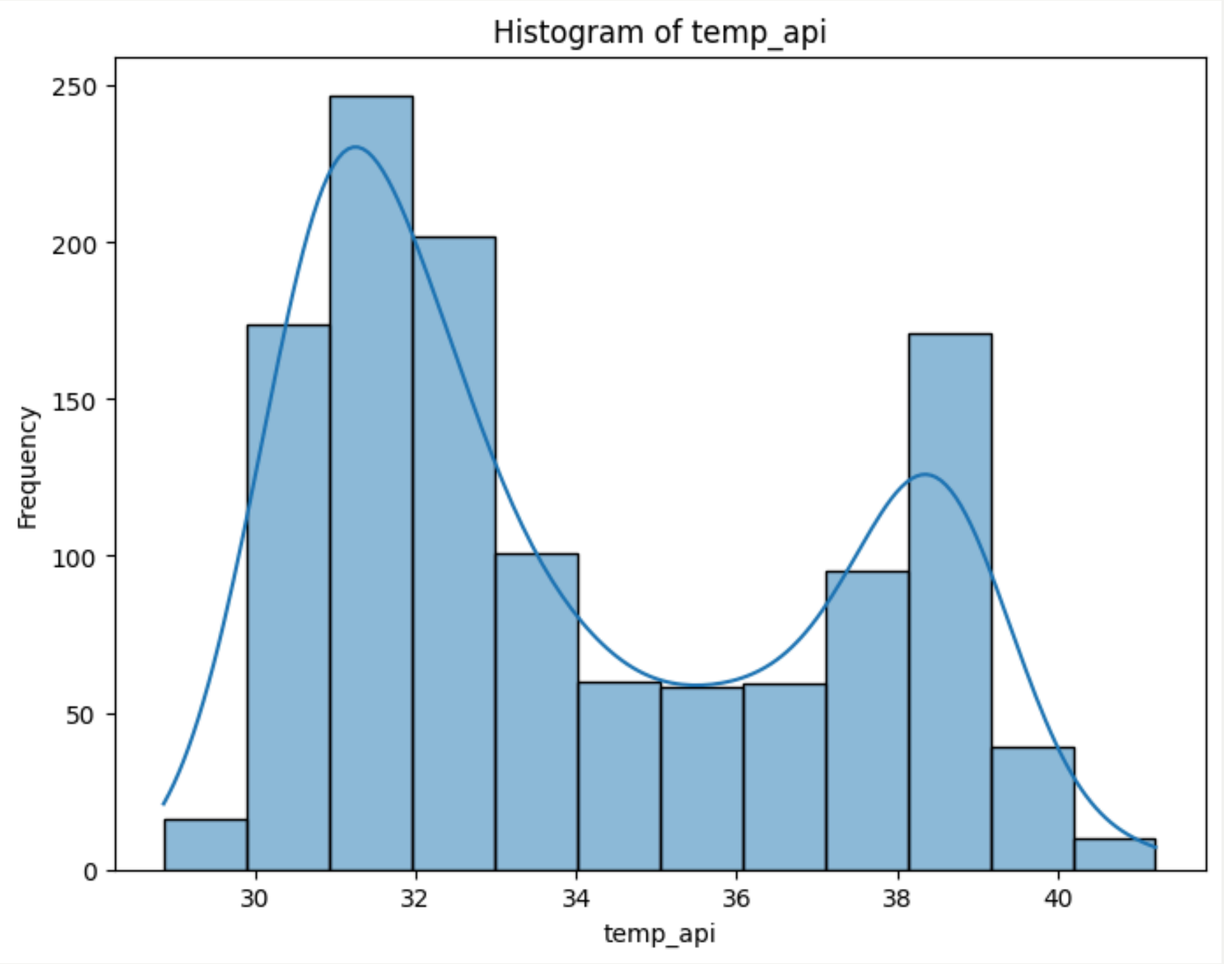
DATA EXPLORATION

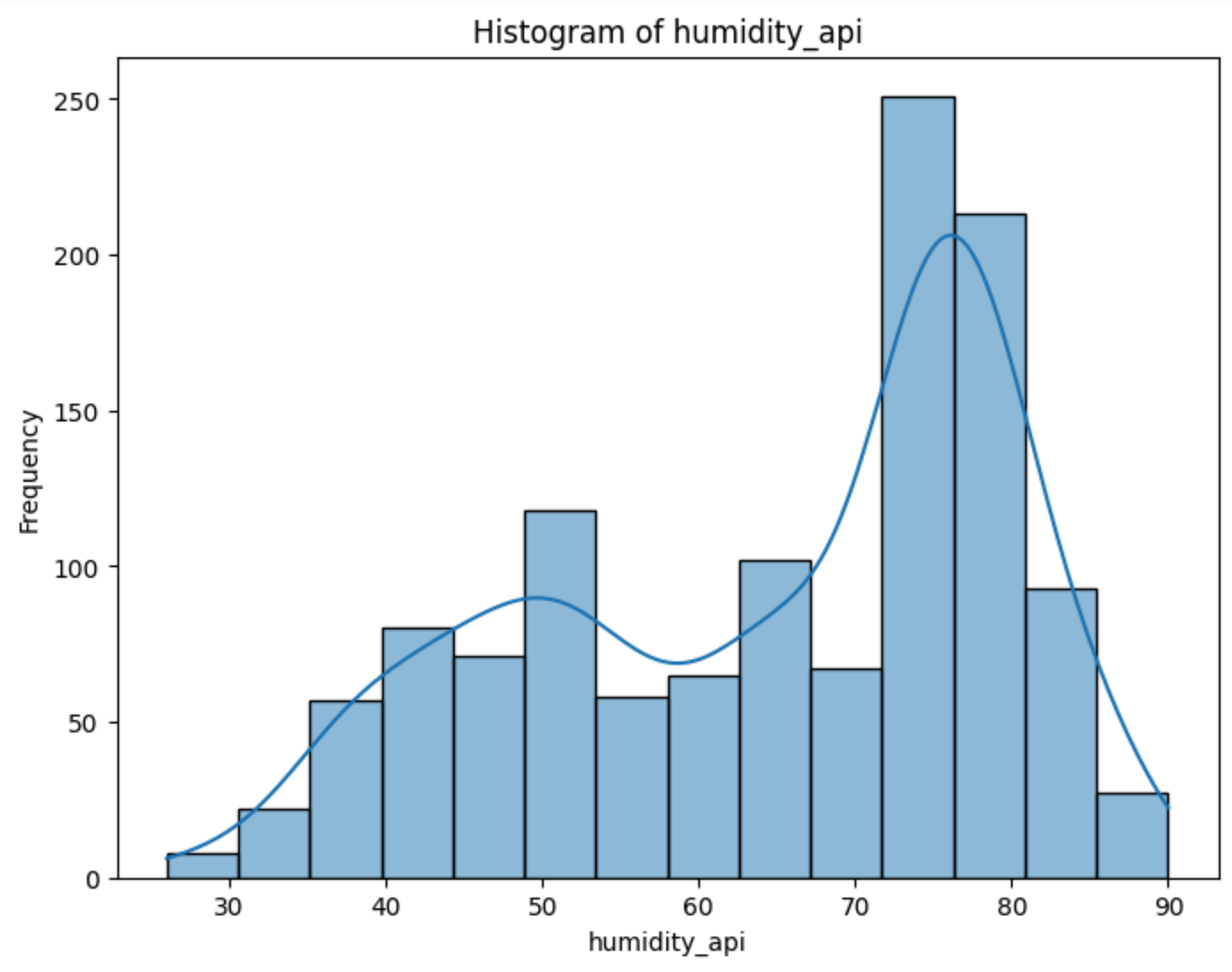
OR NUMERICAL FEATURES USING HISTOGRAM PLOT TO FIND DISTRIBUTION.

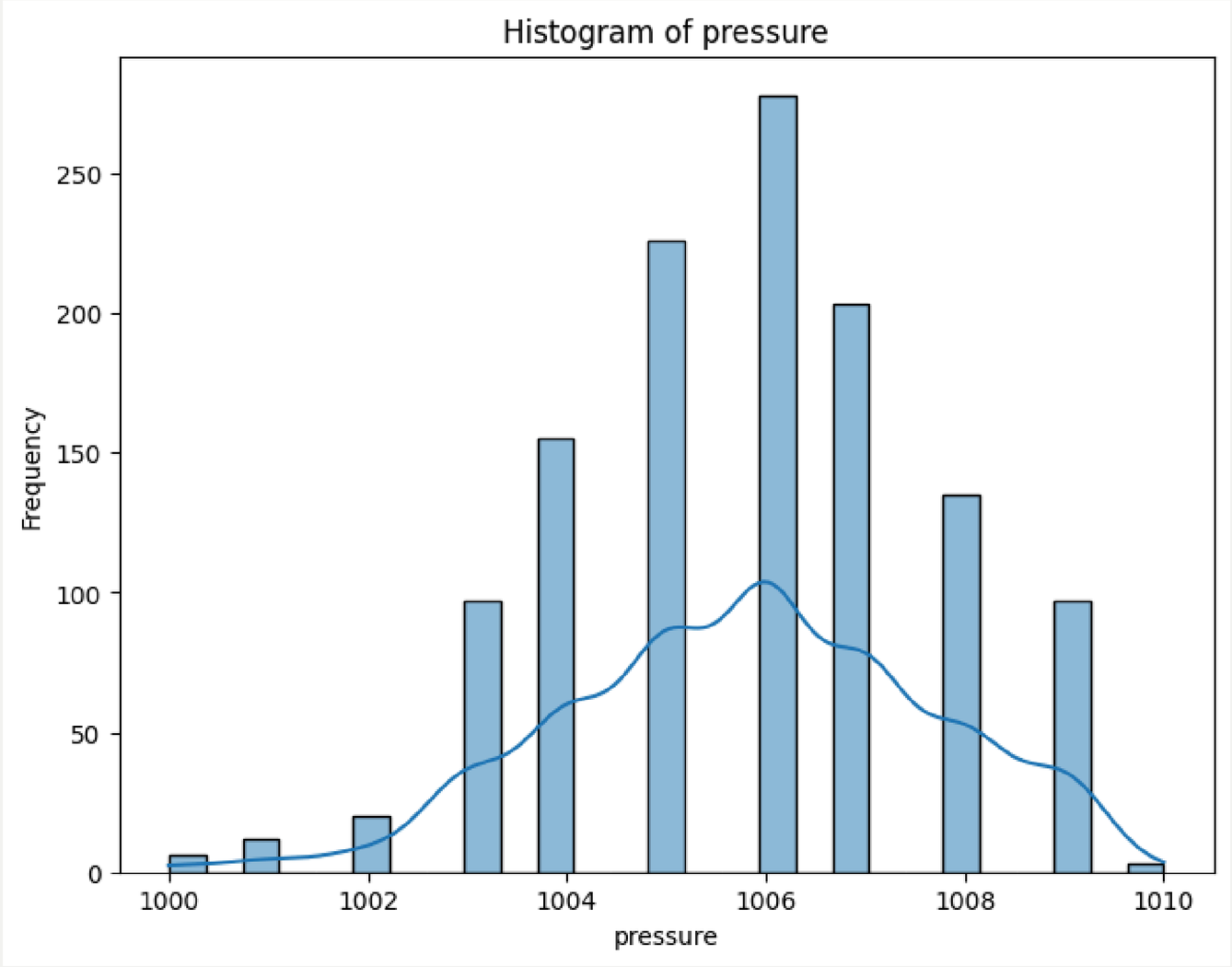


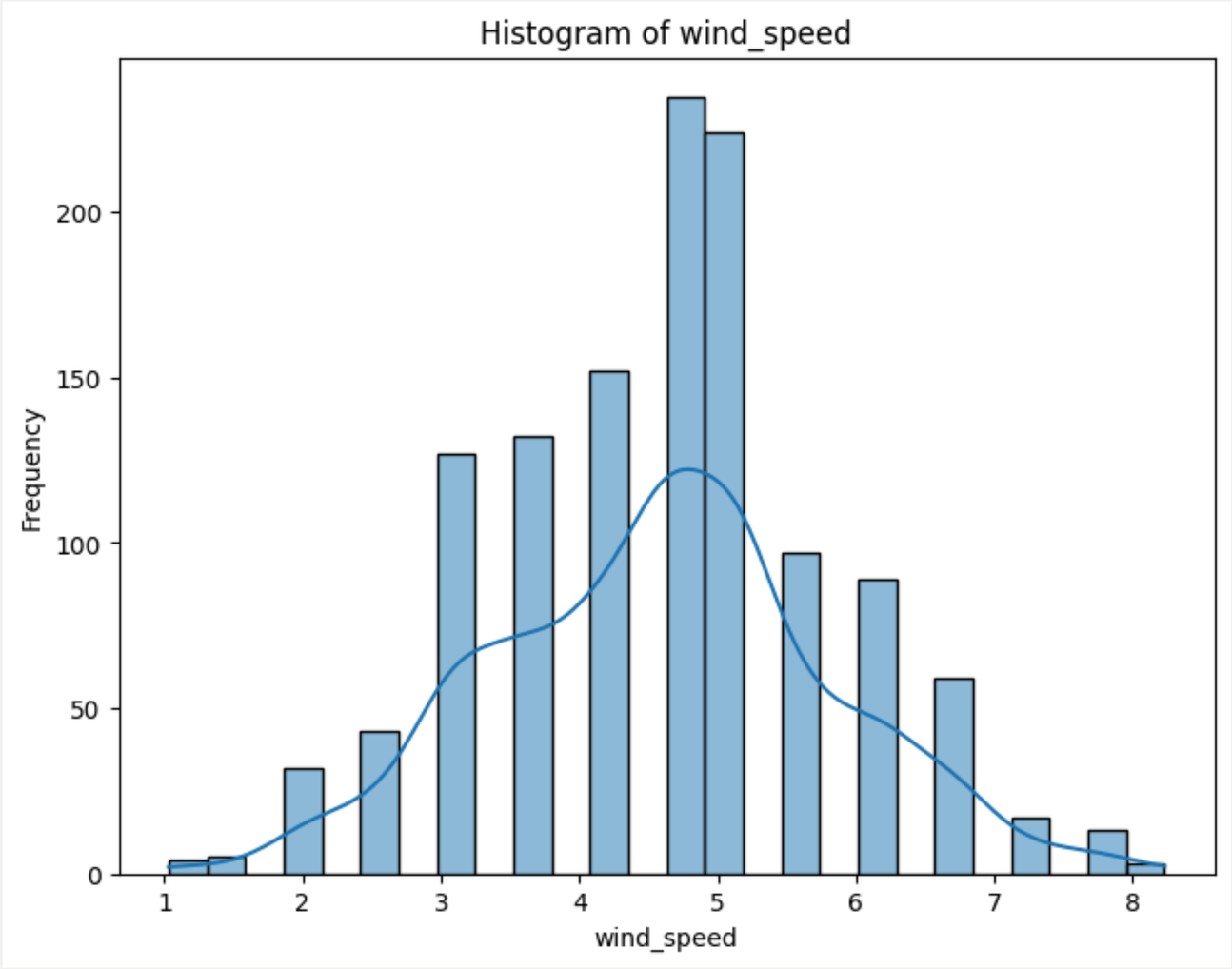

Histogram of humidity_sensor
Frequency
0
50
100
150
200
250
30
40
50
60
70
80
90
humidity_sensor

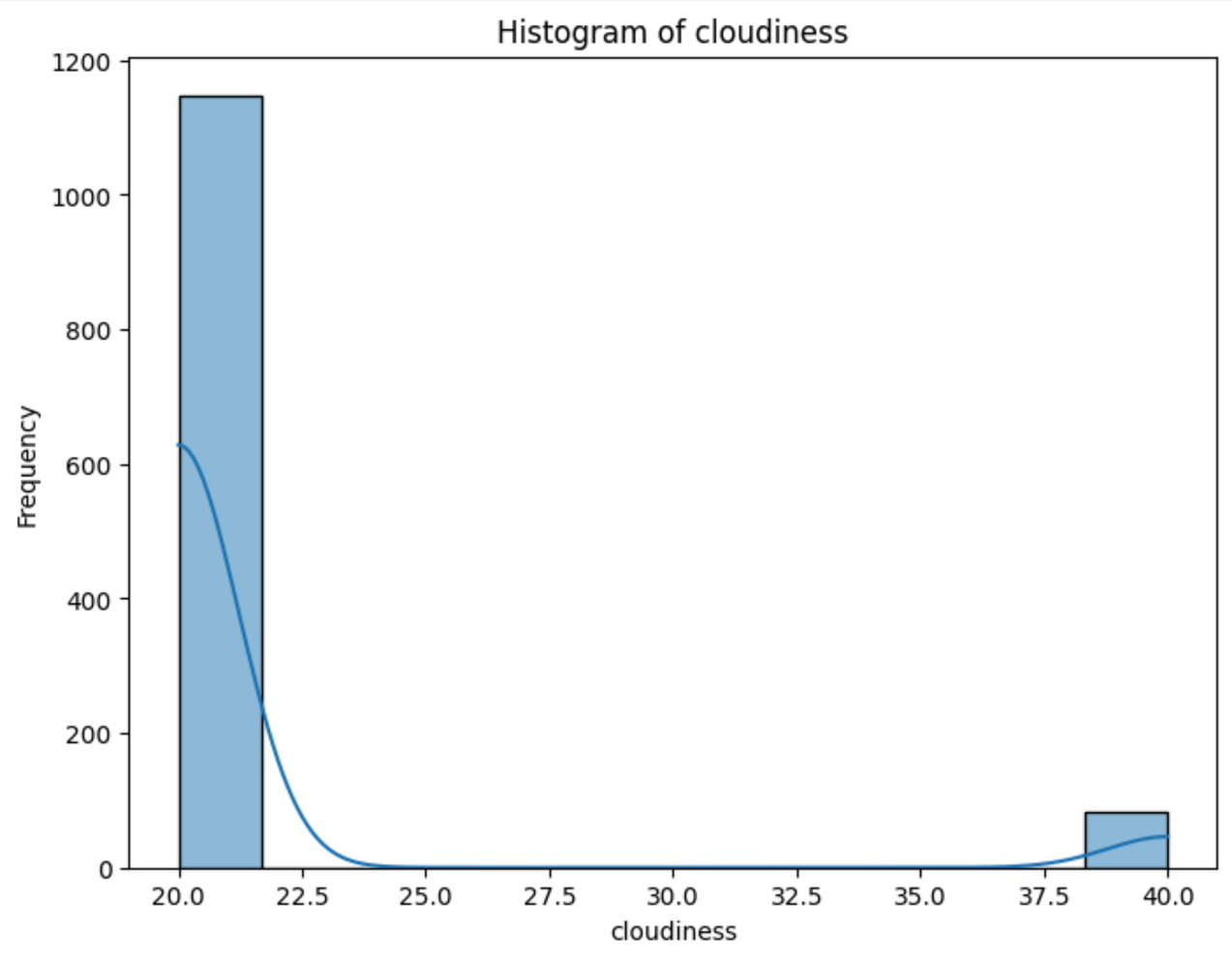

Histogram of temp_sensor
Frequency
0
100
200
300
400
500
22
24
26
28
30
32
34
temp_sensor


Histogram of temp_api
Frequency
250
200
150
100
50
0
30
32
34
36
38
40
temp_api


Histogram of humidity_api
Frequency
0
50
100
150
200
250
30
40
50
60
70
80
90
humidity_api

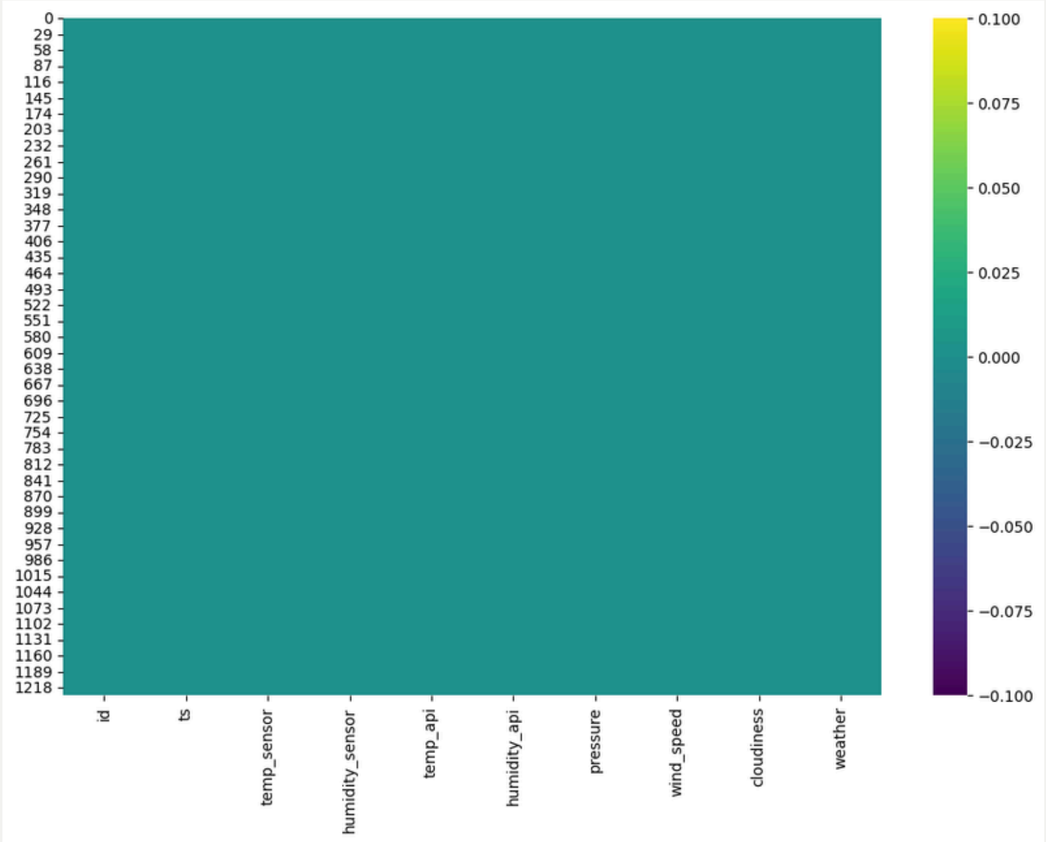

Histogram of pressure
Frequency
0
50
100
150
200
250
1000
1002
1004
1006
1008
1010
pressure


Histogram of wind_speed
Frequency
0
50
100
150
200
1
2
3
4
5
6
7
8
wind_speed


Histogram of cloudiness
Frequency
cloudiness
0
200
400
600
800
1000
1200
20.0
22.5
25.0
27.5
30.0
32.5
35.0
37.5
40.0

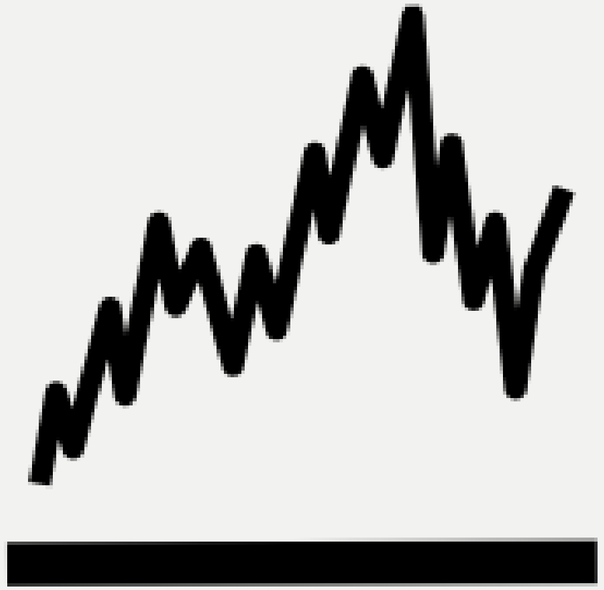
DATA EXPLORATION

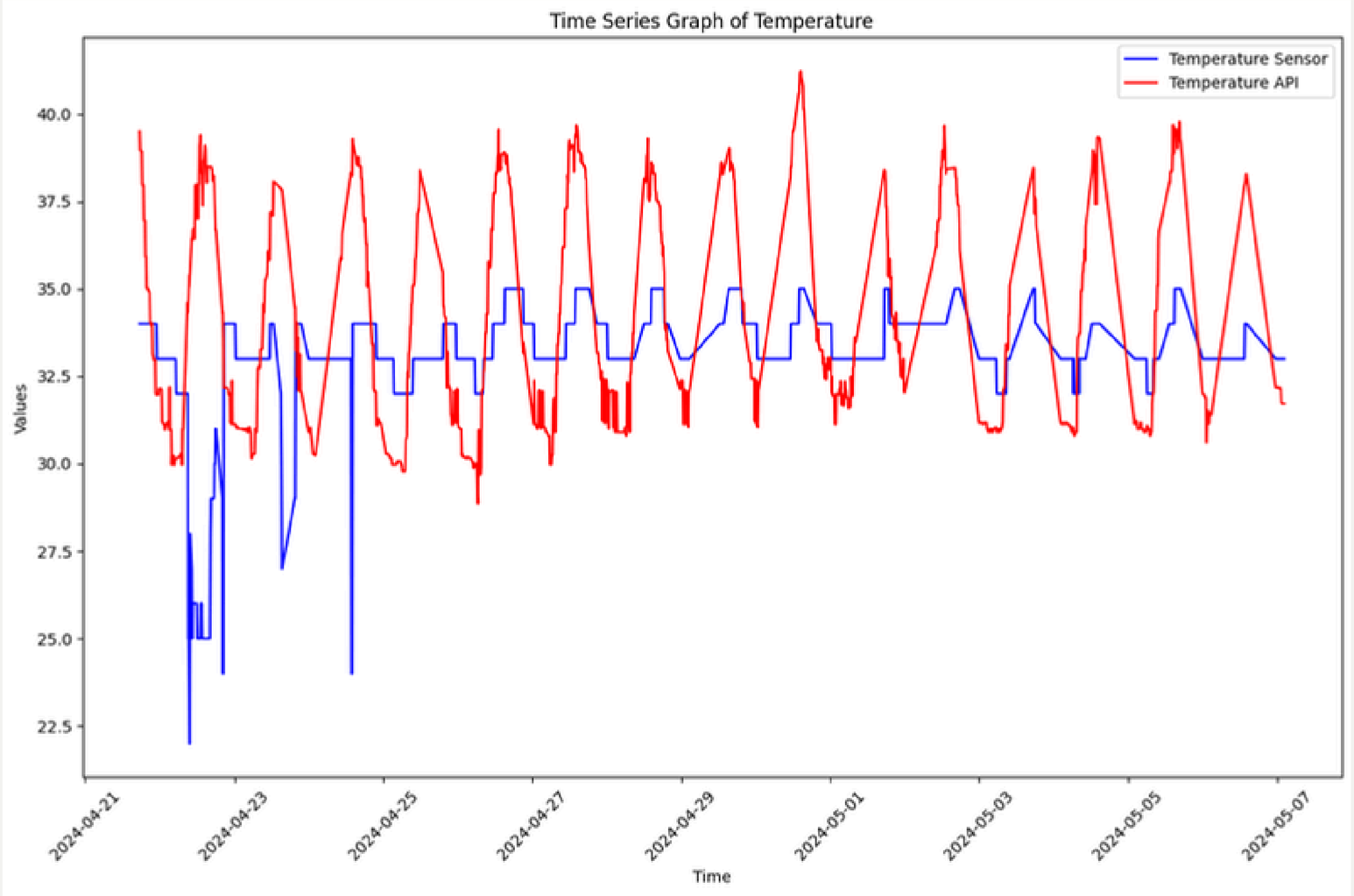
USE HEATMAP TO FIND MISSING DATA.

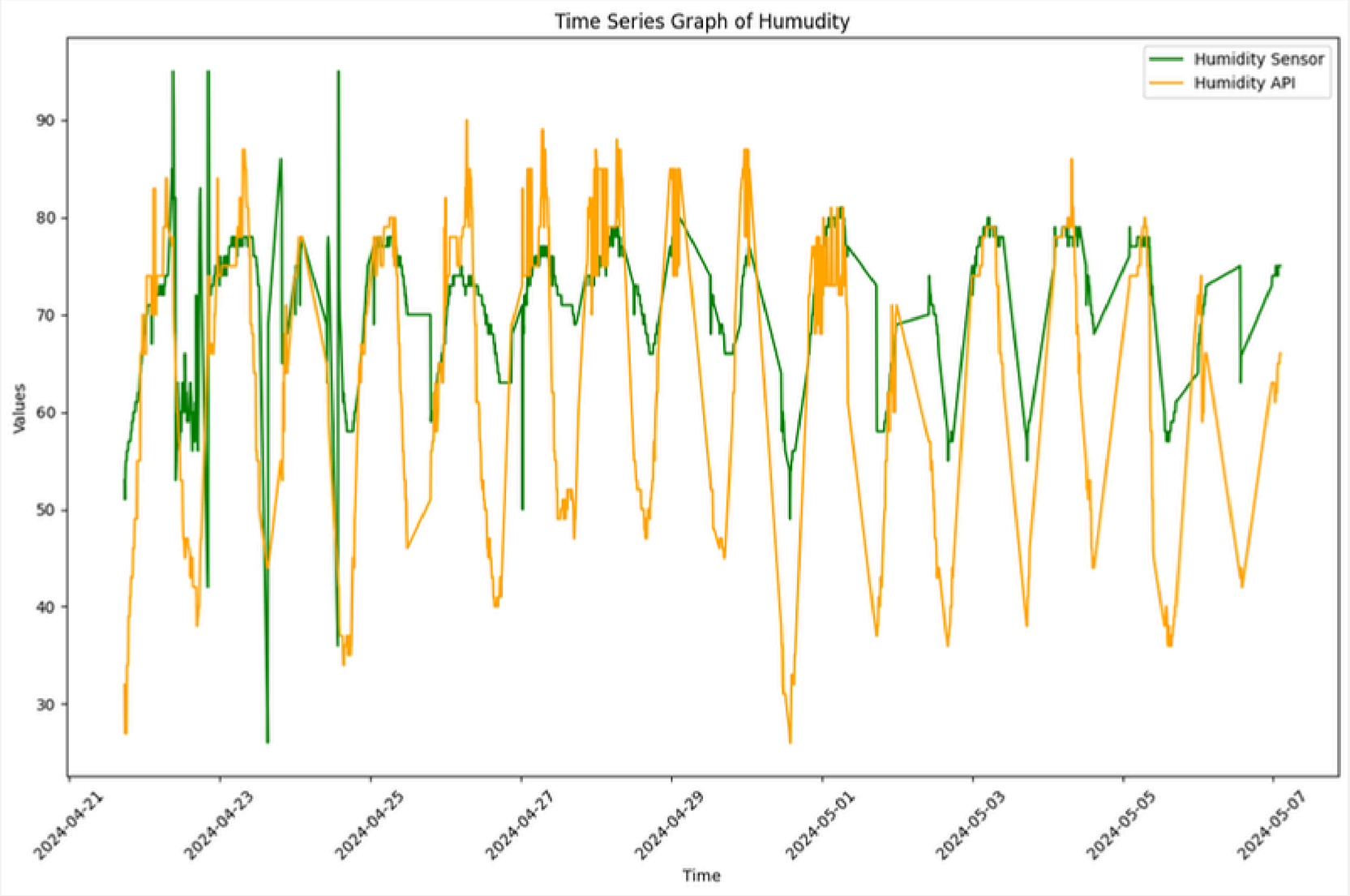


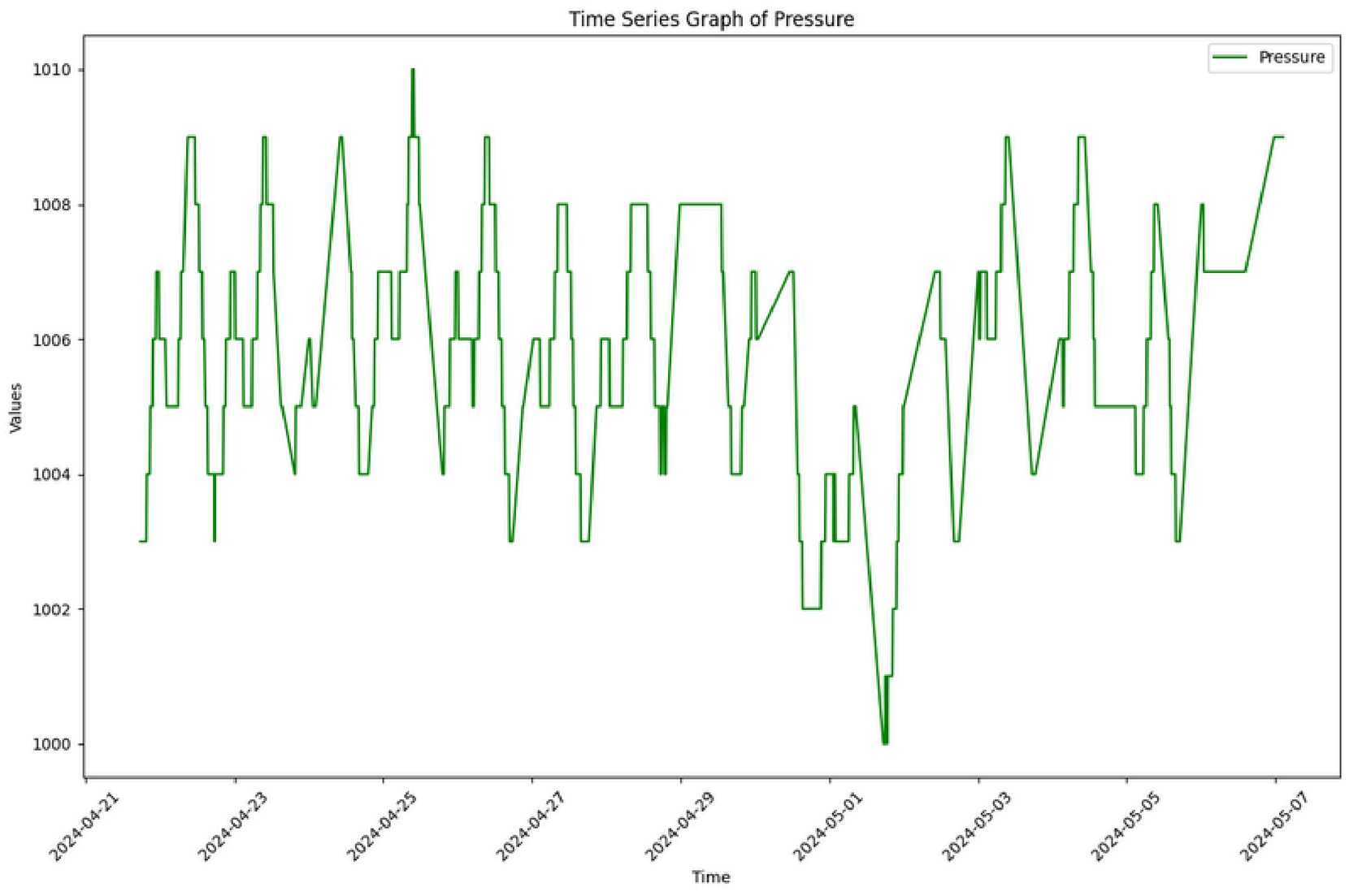
DATA EXPLORATION

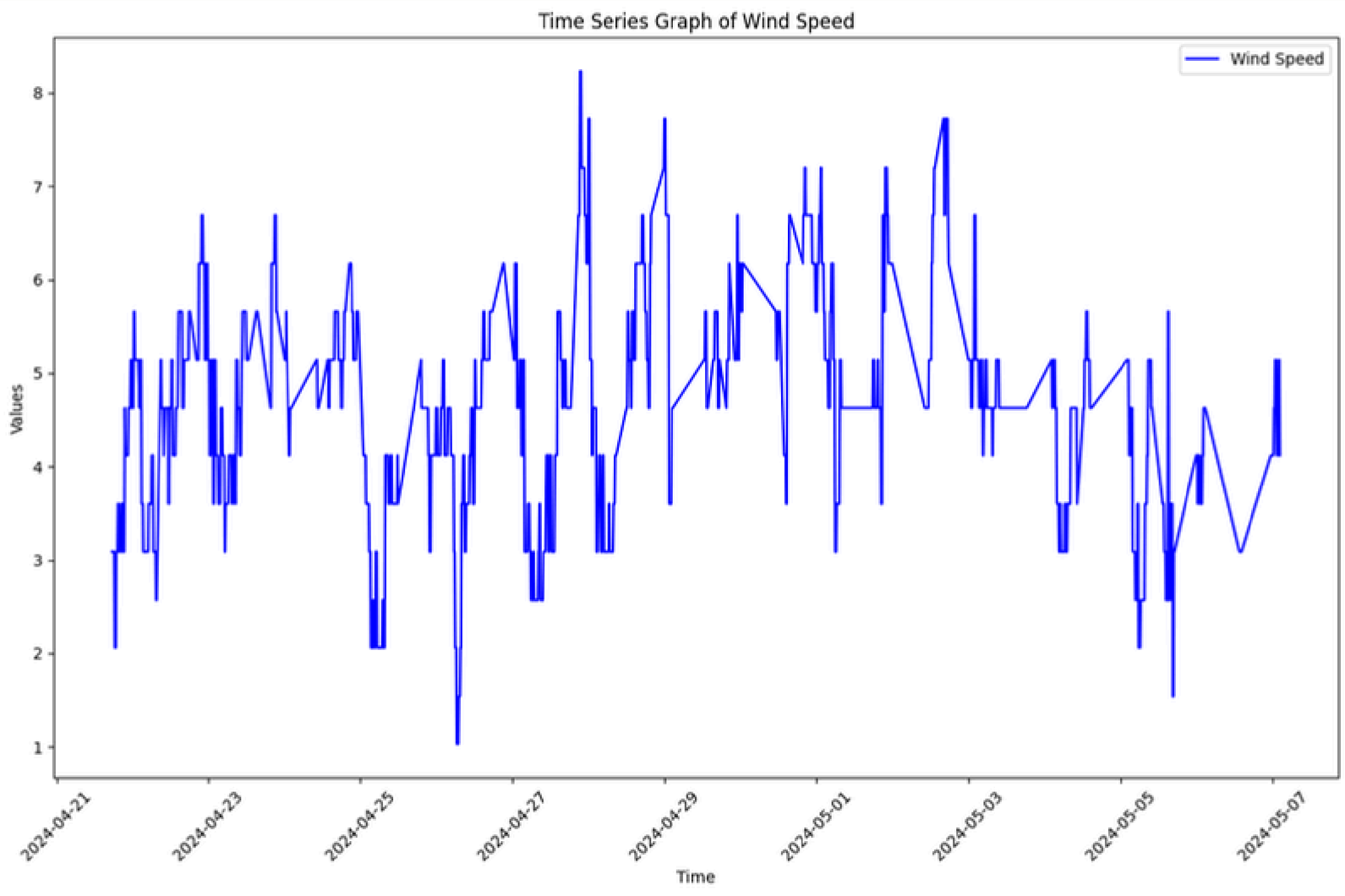
PLOT TIME SERIES GRAPH AMONG NUMERICAL FEATURES TO FIND A TREND OF DATA IN THE FUTURE.




Time Series Graph of Temperature
Temperature Sensor
Temperature API
Values
40.0
37.5
35.0
32.5
30.0
27.5
25.0
22.5
2024-04-21
2024-04-23
2024-04-25
2024-04-27
2024-04-29
2024-05-01
2024-05-03
2024-05-05
2024-05-07
Time

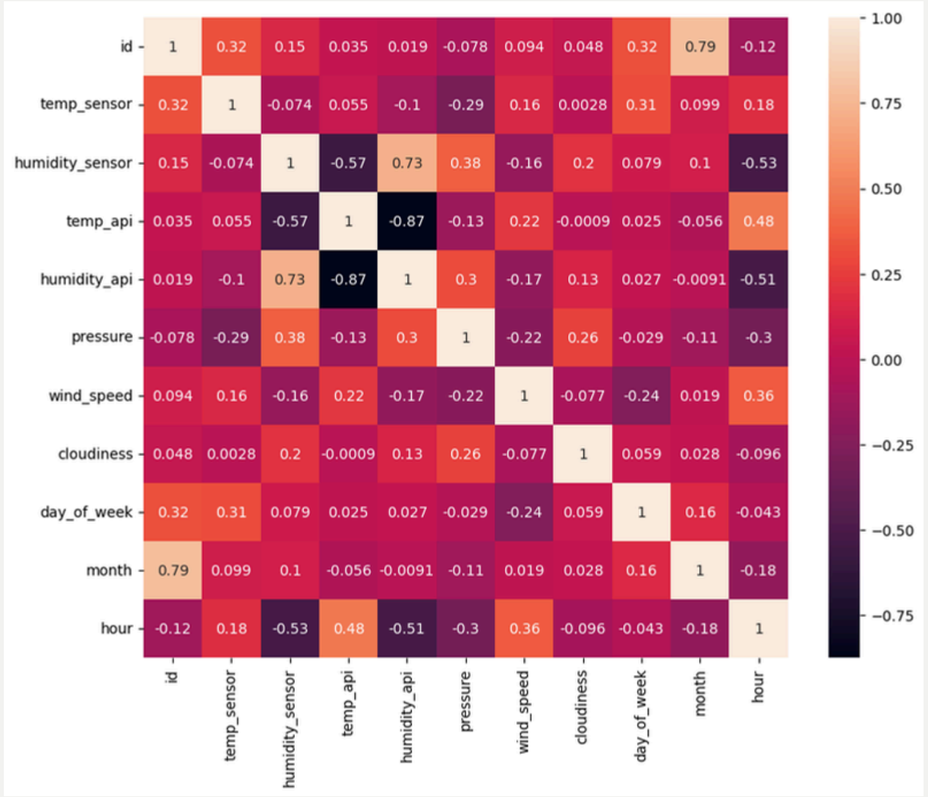

Time Series Graph of Humudity
Humidity Sensor
Humidity API
Values
90
80
70
60
50
40
30
2024-04-21
2024-04-23
2024-04-25
2024-04-27
2024-04-29
2024-05-01
2024-05-03
2024-05-05
2024-05-07
Time


Time Series Graph of Pressure
Pressure
1010
1008
1006
1004
1002
1000
Values
2024-04-21
2024-04-23
2024-04-25
2024-04-27
2024-04-29
2024-05-01
2024-05-03
2024-05-05
2024-05-07
Time


Time Series Graph of Wind Speed
Wind Speed
Values
Time
1
2
3
4
5
6
7
8
2024-04-21
2024-04-23
2024-04-25
2024-04-27
2024-04-29
2024-05-01
2024-05-03
2024-05-05
2024-05-07

DATA EXPLORATION

USE HEATMAP TO SHOW CORRELATION AMONG NUMERICAL FEATURES



DATA PREPROCESSING

DATA PREPROCESSING

CONVERT TS TO NEW COLUMNS DAY_OF_WEEK, MONTH, HOUR THEN DROP TS

```
1  data["day_of_week"] = data["ts"].dt.dayofweek
2  data["month"] = data["ts"].dt.month
3  data["hour"] = data["ts"].dt.hour
4
5  data.drop("ts", axis=1, inplace=True)
6  display(data.head())
```

BECAUSE WE NEED USE THESE DATA COLUMNS FOR TRAINING MODEL

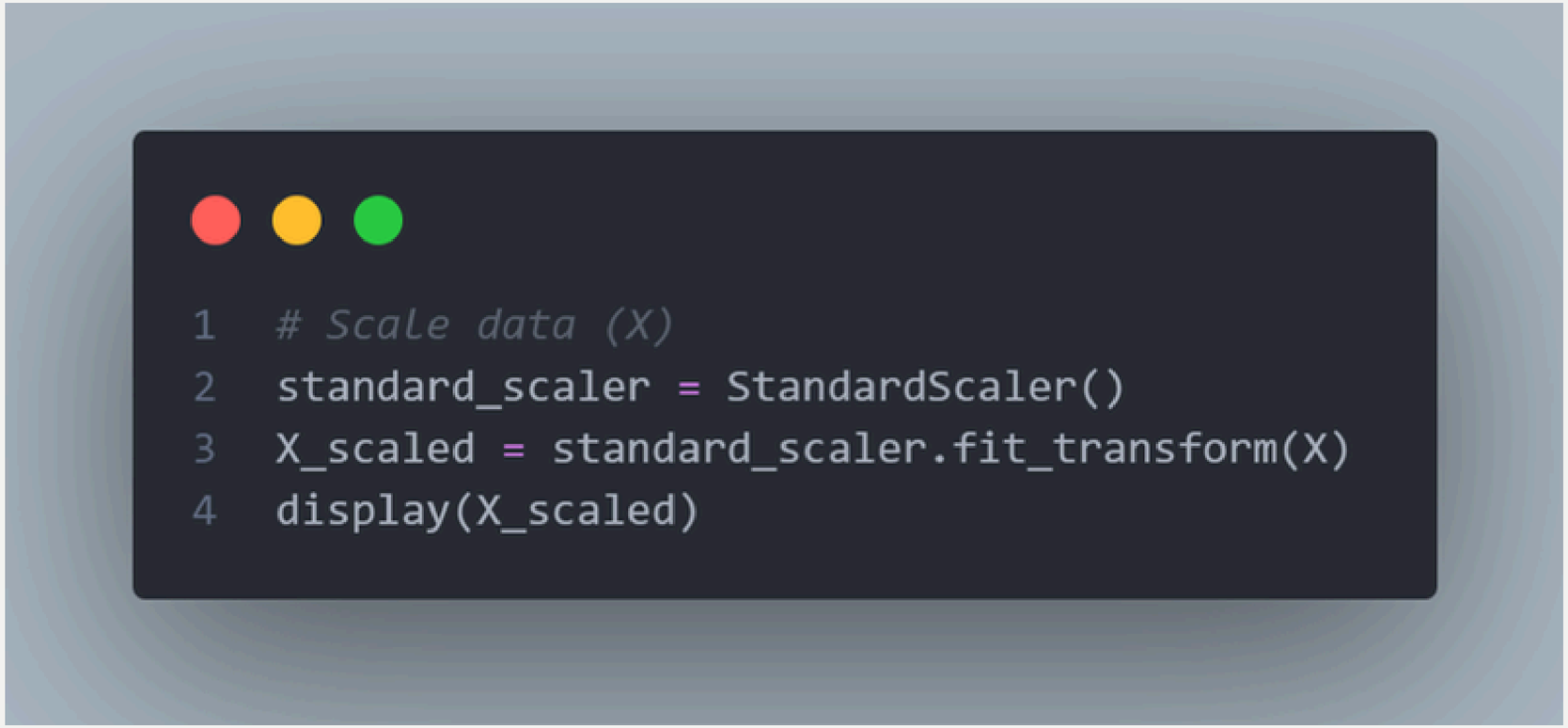
DATA PREPROCESSING

PREDICTOR AND TARGET SPLIT

```
X = data.drop(["weather"], axis=1)
y = data["weather"]
```

DATA PREPROCESSING

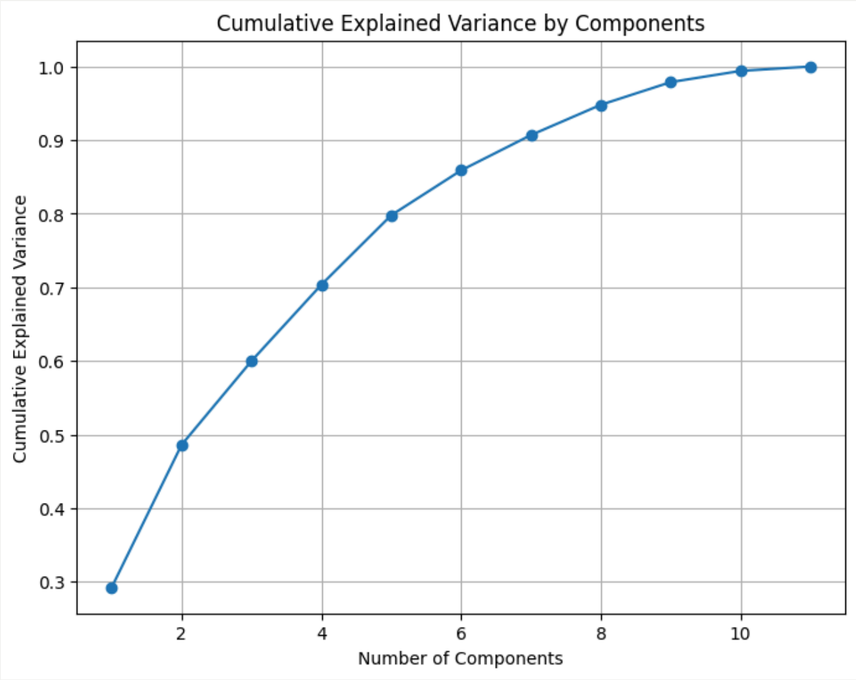
SCALE DATA WITH STANDARD SCALER



```
# Scale data (X)
standard_scaler = StandardScaler()
X_scaled = standard_scaler.fit_transform(X)
display(X_scaled)
```

DATA PREPROCESSING

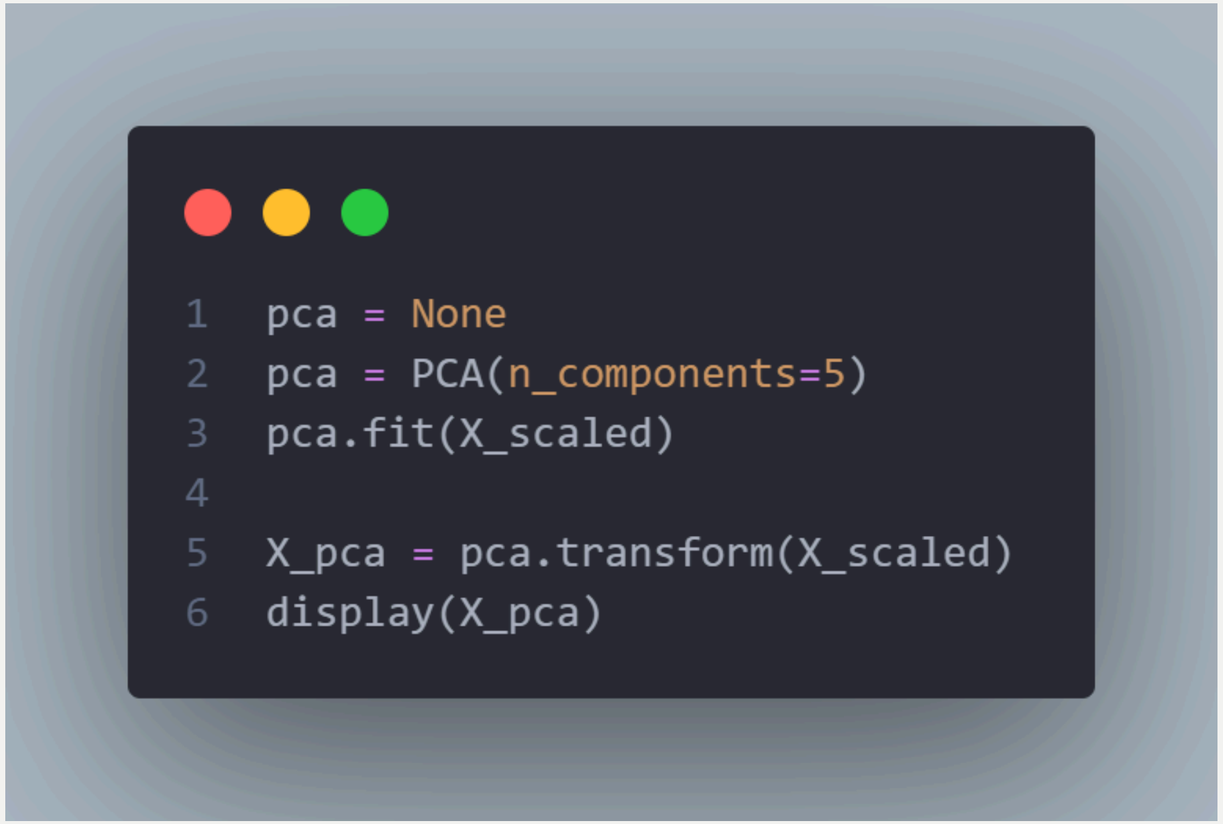
PLOT CUMULATIVE VARIANCE BY COMPONENT



FROM PLOT WE SELECT NUMBER OF COMPONENT IS 5 BECAUSE IT NEAR TO 80 PERCENT

DATA PREPROCESSING

THEN WE ADAPT PCA 5 COMPONENTS TO OUR DATA



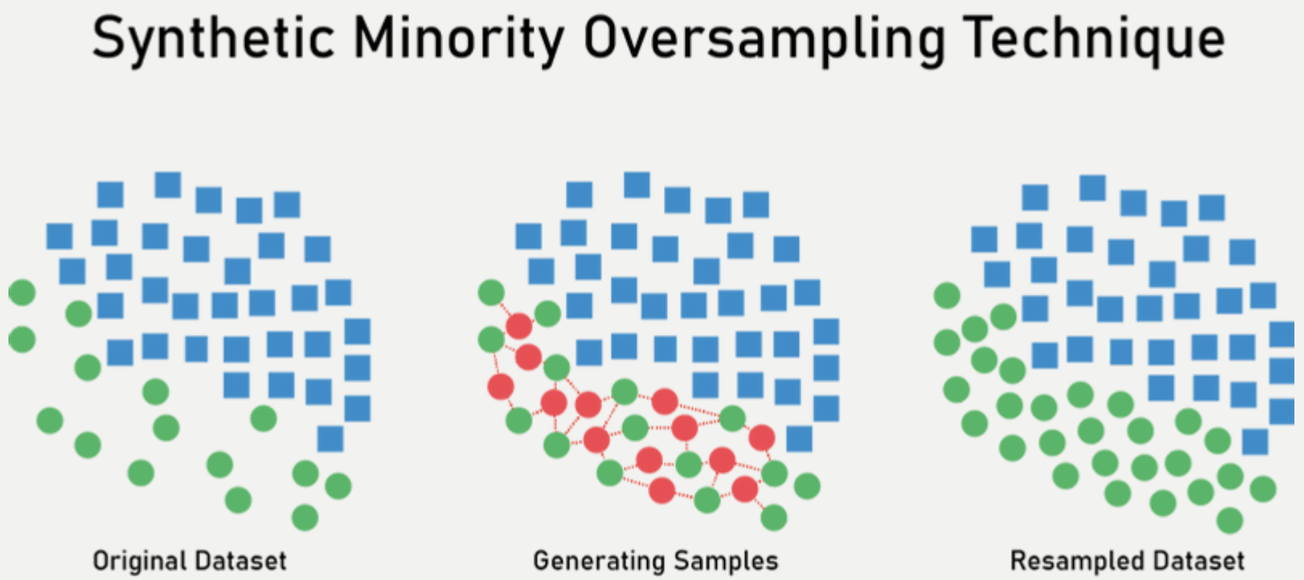
```
pca = None
pca = PCA(n_components=5)
pca.fit(X_scaled)

X_pca = pca.transform(X_scaled)
display(X_pca)
```

IMBALANCED DATA

refers to a situation in classification problems where the distribution of classes in the dataset is highly skewed, meaning that one class is significantly more prevalent than the others. This imbalance can lead to biased models that perform poorly in accurately predicting the minority class, as the model may become overly biased towards the majority class.

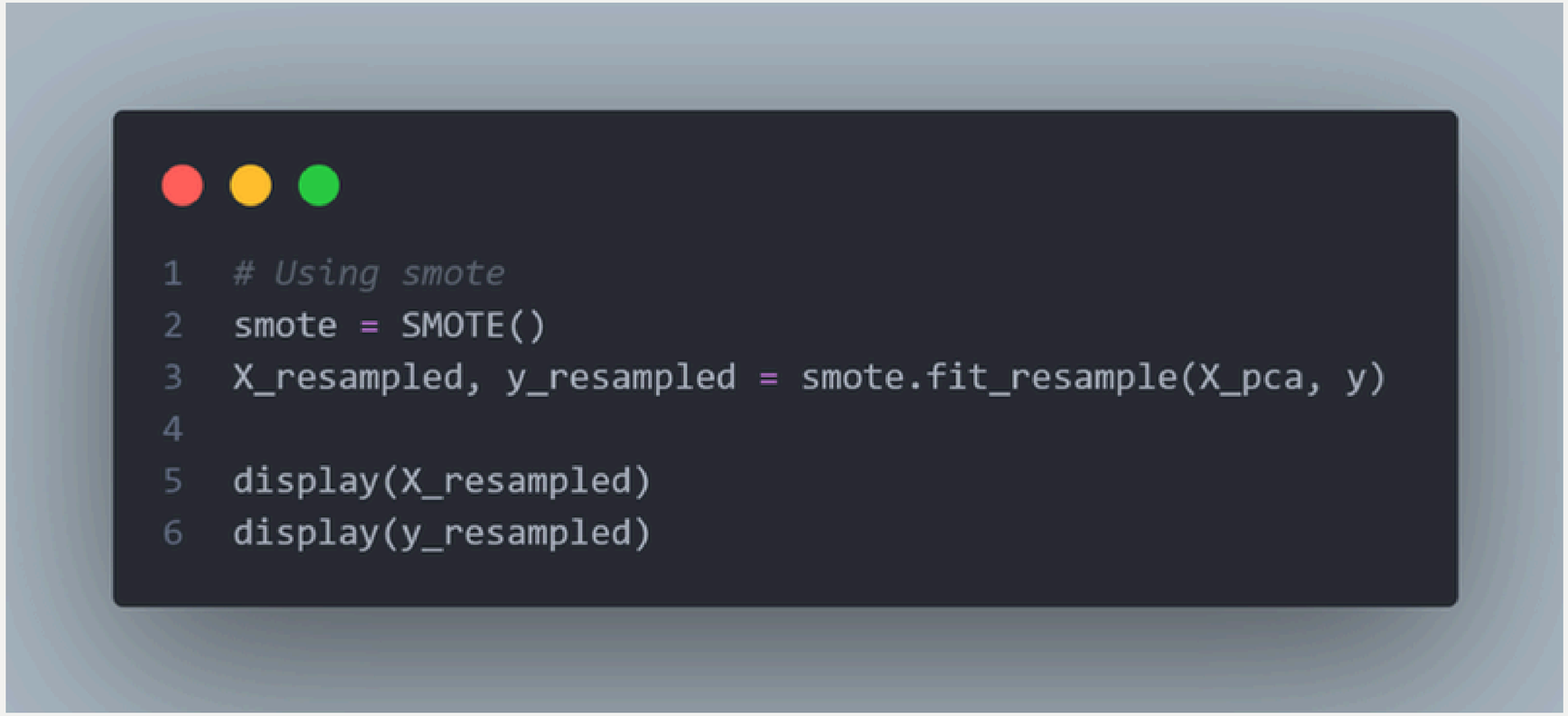
SMOTE

(Synthetic Minority Over-sampling Technique) is a method used to address class imbalance in datasets by generating synthetic examples of the minority class. It works by creating new synthetic instances along the line segments joining existing minority class instances, thereby balancing the class distribution and improving the performance of machine learning models on imbalanced datasets.



WHY SMOTE?

During summer, our data collection predominantly reflects sunny conditions with fewer instances of rain. This imbalance can arise due to the larger volume of sunny data compared to rainy data.



```
# Using smote
smote = SMOTE()
X_resampled, y_resampled = smote.fit_resample(X_pca, y)

display(X_resampled)
display(y_resampled)
```

MODELING PART

RANDOM FOREST

We use Random Forest classification techniques to predict weather because Random Forest is a type of machine learning that creates a group of decision trees. It's straightforward to use and often gives excellent results without needing fine-tuning.

PROS

- Versatility: Random Forests can do both classification and regression tasks.
- Data Compatibility: Works with categorical and numerical data without needing scaling.
- Feature Selection: Automatically picks relevant features.
- Outlier Resilience: Handles outliers well.
- Relationship Handling: Works with linear and non-linear relationships.
- Accuracy: Often provides high accuracy.
- Bias-Variance Balance: Balances bias and variance effectively.

CONS

- Interpretability: Not easy to interpret like linear regression.
- Computationally Intensive: Can be slow for large datasets.
- Black Box Nature: Limited control over model workings.

MODELING

SPLIT TRAIN TEST TECHNIQUE

```
1  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
```

MODELING

USE LABELENCODER TO ENCODE Y_TRAIN

```
label_encoder = LabelEncoder()
y_train_encoded = label_encoder.fit_transform(y_train)
display(y_train_encoded)
```

MODELING

GRID SEARCH CV TECHNIQUE

```python
param_grid = {
    'n_estimators': range(10, 201, 10)
}

# Create a Random Forest classifier
rf_classifier = RandomForestClassifier(random_state=1)

# Perform grid search with cross-validation
grid_search = GridSearchCV(estimator=rf_classifier, param_grid=param_grid, cv=5, scoring='accuracy')
grid_search.fit(X_train, y_train_encoded)

# Get the best parameters and best score
best_n_estimators = grid_search.best_params_['n_estimators']
best_score = grid_search.best_score_

print("Best Number of Estimators:", best_n_estimators)
print("Best Accuracy Score:", best_score)
```

TO FIND BEST K FOR RANDOM FOREST

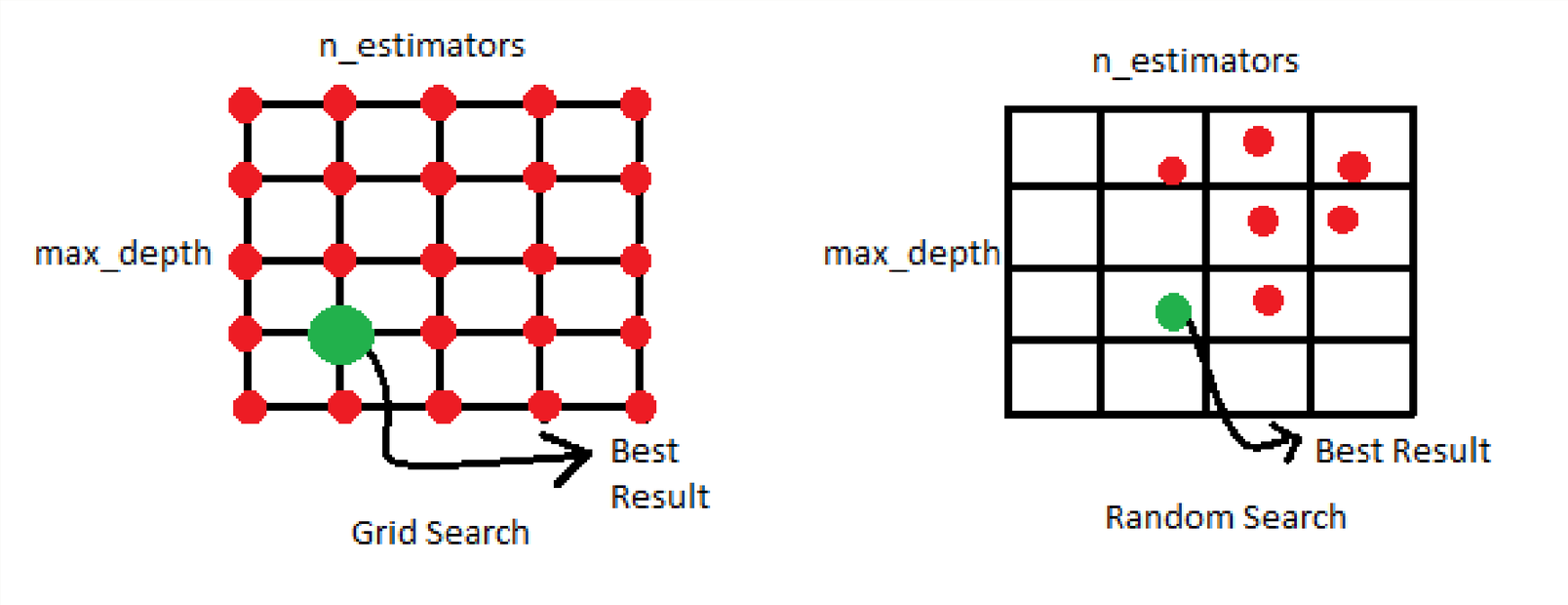
MODELING

TRAIN MODEL WIL BEST K

```
rf_classifier = None
rf_classifier = RandomForestClassifier(n_estimators=best_n_estimators, random_state=1)
rf_classifier.fit(X_train, y_train_encoded)
```

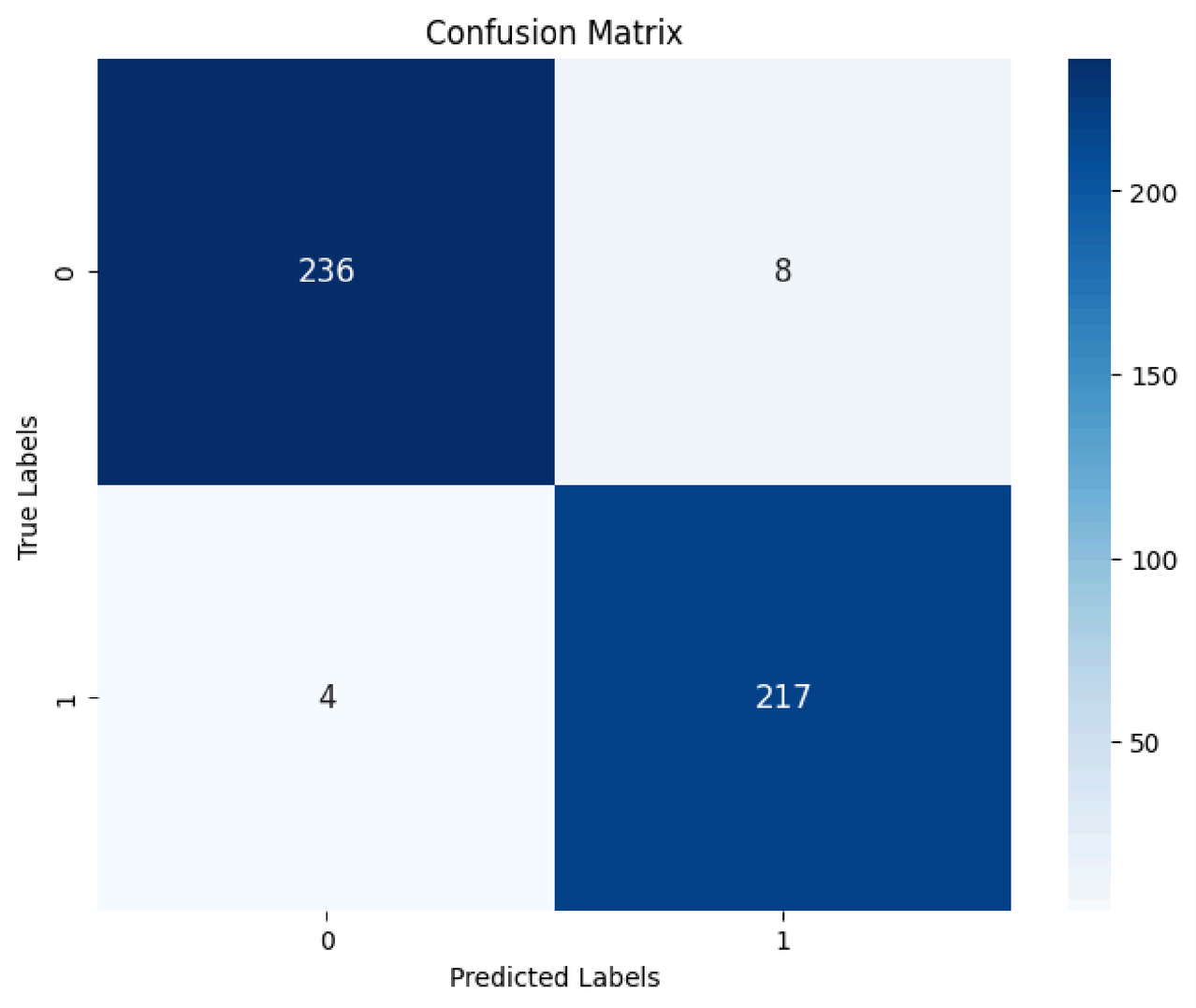
GRID SEARCH CV

helps find the best settings for a model by trying different options and picking the one that works best. It's like testing different ingredients for a recipe to make the tastiest dish.



EVALUATE THE MODEL PART

```
Accuracy: 0.9741935483870968
------------------------------------------------------------
Classification Report:
              precision    recall  f1-score   support

      Clouds       0.98      0.97      0.98       244
        Rain       0.96      0.98      0.97       221

    accuracy                           0.97       465
   macro avg       0.97      0.97      0.97       465
weighted avg       0.97      0.97      0.97       465

------------------------------------------------------------
Confusion Matrix:
 [[236   8]
 [  4 217]]
```

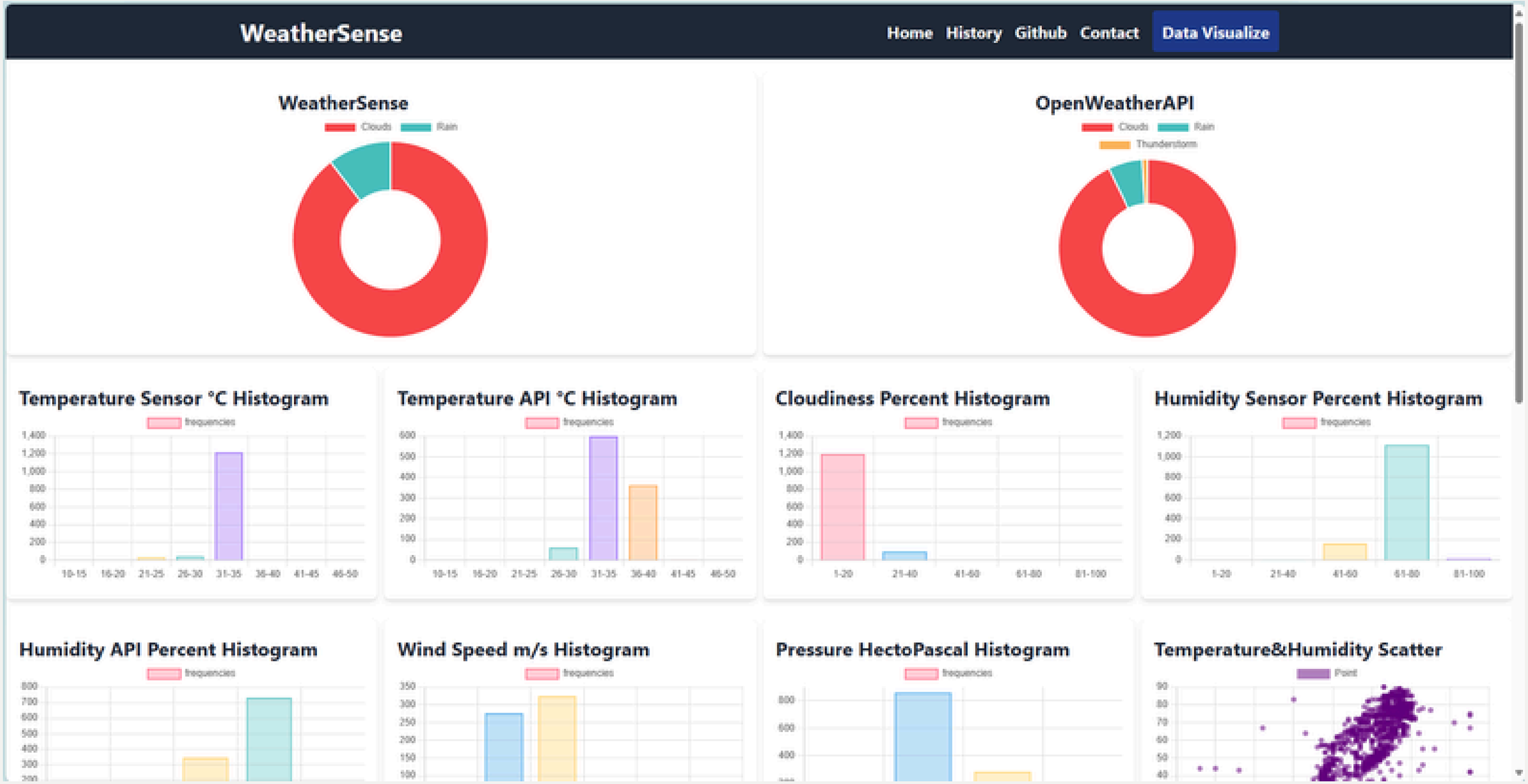

Confusion Matrix
236
8
4
217
0
1
True Labels
0
1
Predicted Labels
200
150
100
50

POSSIBLE APPLICATION

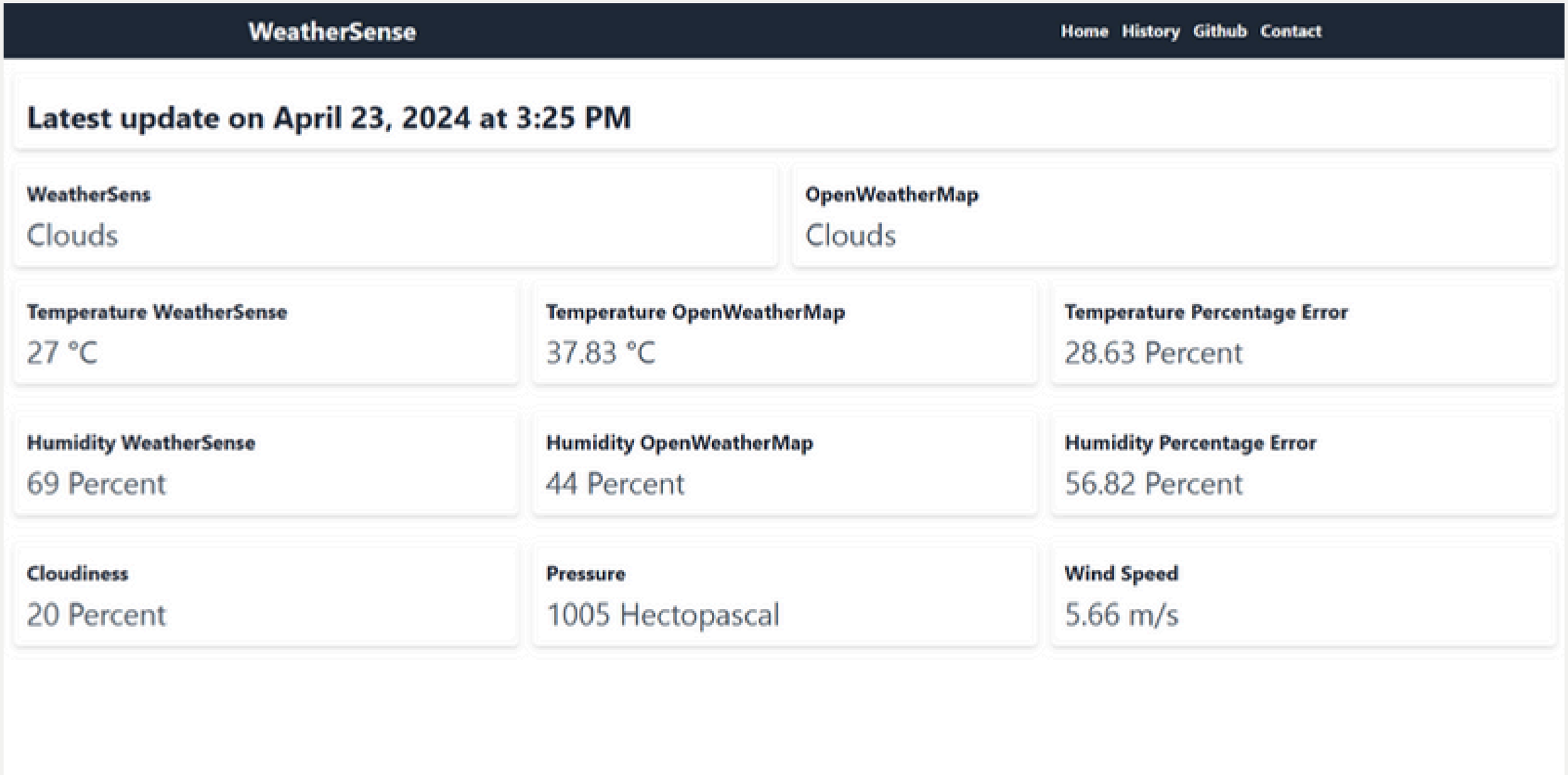
POSSIBLE APPLICATION

- Forecasting: Providing accurate weather forecasts for various locations and time intervals, helping individuals and organizations plan their activities accordingly.
- Agriculture: Assisting farmers in making informed decisions about planting, harvesting, irrigation, and pest control based on weather predictions.
- Travel : Helping travelers plan their trips by providing weather forecasts for their destinations, ensuring they have a pleasant experience.
- Transportation: Enhancing transportation safety and efficiency by predicting weather-related hazards such as storms, heavy rainfall, or snowfall.

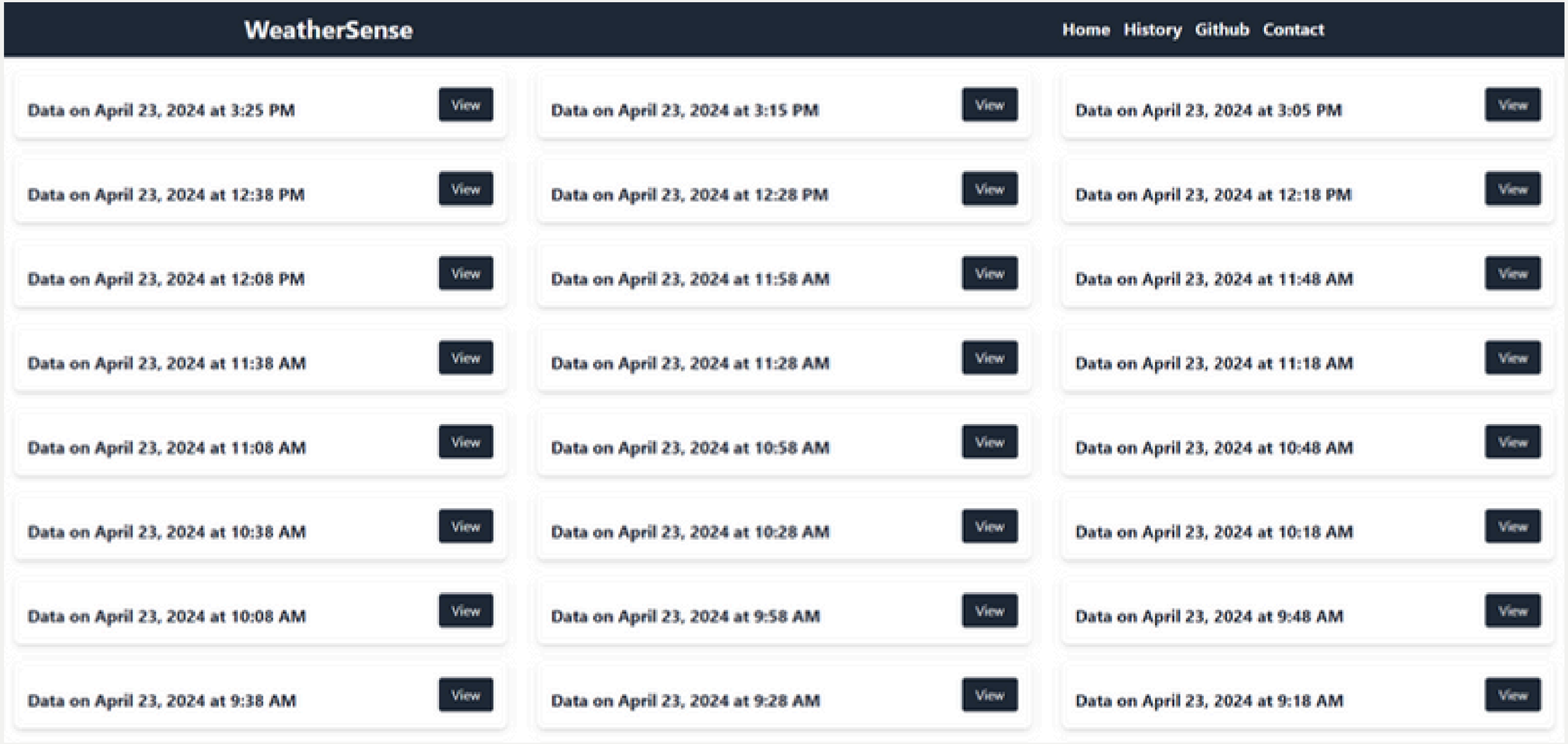
WEATHERSENSE SHOWCASE



WEATHERSENSE SHOWCASE



WEATHERSENSE SHOWCASE



REFERRENCE

https://medium.datadriveninvestor.com/random-forest-pros-and-cons-c1c42fb64f04

https://www.google.com/url?q=https://ntcloudsolutions.ntplc.co.th/knowledge/imbalanced-data-classification/&sa=D&source=editors&ust=1715032692718357&usg=AOvVaw2gaN-D_Gew2hcDg0nF9Z7Z

PROJECT MEMBER

1. WISSARUT KANASUB

2. SUKPRACHOKE LEELAPISUTH (DROPPED)