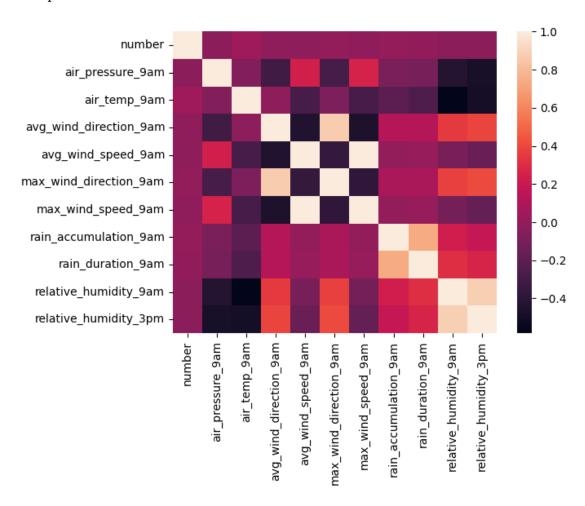
## decision-tree1

## November 10, 2024

```
[]: #Step-1: Begin the tree with the root node, says S, which contains the complete
      \rightarrow dataset.
     #Step-2: Find the best attribute in the dataset using Attribute Selection
      \hookrightarrow Measure (ASM).
     #Step-3: Divide the S into subsets that contains possible values for the best<sub>11</sub>
      ⇔attributes.
     #Step-4: Generate the decision tree node, which contains the best attribute.
     \#Step-5: Recursively make new decision trees using the subsets of the dataset
      \hookrightarrow created in step -3.
     #Continue this process until a stage is reached where you cannot further_
      ⇔classify the nodes and
     #called the final node as a leaf node.
[7]: import pandas as pd
     from sklearn.metrics import accuracy_score,confusion_matrix
     from sklearn.model_selection import train_test_split
     from sklearn.tree import DecisionTreeClassifier
     import os
[8]: df=pd.read_csv("E:\DATASET/daily_weather.csv")
     df.head(10)
[8]:
                air_pressure_9am air_temp_9am avg_wind_direction_9am \
        number
     0
             0
                      918.060000
                                      74.822000
                                                              271.100000
     1
             1
                      917.347688
                                      71.403843
                                                               101.935179
     2
             2
                      923.040000
                                      60.638000
                                                               51.000000
     3
             3
                                      70.138895
                      920.502751
                                                               198.832133
     4
             4
                      921.160000
                                      44.294000
                                                              277.800000
             5
     5
                      915.300000
                                      78.404000
                                                              182.800000
     6
             6
                      915.598868
                                      70.043304
                                                              177.875407
             7
     7
                      918.070000
                                      51.710000
                                                              242.400000
     8
             8
                      920.080000
                                      80.582000
                                                               40.700000
     9
             9
                      915.010000
                                      47.498000
                                                              163.100000
        avg_wind_speed_9am max_wind_direction_9am max_wind_speed_9am
                  2.080354
     0
                                         295,400000
                                                                 2.863283
     1
                  2.443009
                                         140.471548
                                                                 3.533324
```

```
2
                   17.067852
                                            63.700000
                                                                  22.100967
      3
                    4.337363
                                           211.203341
                                                                   5.190045
      4
                    1.856660
                                           136.500000
                                                                   2.863283
      5
                    9.932014
                                           189.000000
                                                                  10.983375
      6
                    3.745587
                                           186.606696
                                                                   4.589632
      7
                    2.527742
                                           271.600000
                                                                   3.646212
      8
                    4.518619
                                            63.000000
                                                                   5.883152
      9
                                           195.900000
                    4.943637
                                                                   6.576604
         rain_accumulation_9am
                                 rain_duration_9am
                                                      relative_humidity_9am
      0
                           0.00
                                                0.0
                                                                   42.420000
                           0.00
      1
                                                0.0
                                                                   24.328697
      2
                           0.00
                                               20.0
                                                                    8.900000
      3
                           0.00
                                                0.0
                                                                   12.189102
      4
                           8.90
                                            14730.0
                                                                   92.410000
      5
                           0.02
                                              170.0
                                                                   35.130000
      6
                           0.00
                                                0.0
                                                                   10.657422
      7
                           0.00
                                                0.0
                                                                   80.470000
      8
                           0.00
                                                0.0
                                                                   29.580000
      9
                           0.00
                                                0.0
                                                                   88,600000
         relative_humidity_3pm
      0
                      36.160000
      1
                      19.426597
      2
                      14.460000
      3
                      12.742547
                      76.740000
      4
      5
                      33.930000
      6
                      21.385657
      7
                      74.920000
      8
                      24.030000
      9
                      68.050000
 [9]:
     df.columns
 [9]: Index(['number', 'air_pressure_9am', 'air_temp_9am', 'avg_wind_direction_9am',
              'avg_wind_speed_9am', 'max_wind_direction_9am', 'max_wind_speed_9am',
             'rain_accumulation_9am', 'rain_duration_9am', 'relative_humidity_9am',
              'relative_humidity_3pm'],
            dtype='object')
[10]: df.shape
[10]: (1095, 11)
[31]: import seaborn as sns
      sns.heatmap(df.corr())
```

## [31]: <AxesSubplot:>



[11]:	<pre>df[df.isnull().any(axis=1)].head()</pre>										
[11]:		number	air_pressure_9am	air_temp_9am	avg_wind_direction_9am	\					
	16	16	917.890000	NaN	169.200000						

	169.200000	Nan	890000	16 917.8	10	
	182.600000	58.820000	290000	111 915.2	111	
	183.300000	NaN	900000	177 915.9	177	
	47.737753	58.380598	596607	262 923.5	262	
	194.400000	62.600000	480000	277 920.4	277	
\	max_wind_speed_9am	rind_direction_9am	max_wi	avg_wind_speed_9am		
	2.930391	196.800000		2.192201	16	
	NaN	189.000000		15.613841	111	
	5.346287	189.900000		4.719943	177	
	13.671423	67.145843		10.636273	262	
	3.869906	NaN		2.751436	277	
	0.003300	Ivaiv		2.101100		

```
rain_accumulation_9am rain_duration_9am relative_humidity_9am \
      16
                             0.0
                                                 0.0
                                                                   48.990000
                             0.0
                                                 0.0
                                                                   21.500000
      111
      177
                             0.0
                                                 0.0
                                                                   29.260000
      262
                             0.0
                                                 NaN
                                                                   17.990876
      277
                             0.0
                                                 0.0
                                                                   52.580000
           relative_humidity_3pm
      16
                       51.190000
      111
                       29.690000
      177
                       46.500000
      262
                       16.461685
      277
                       54.030000
[12]: df=df.dropna()
      df.shape
[12]: (1064, 11)
[13]: clean df=df.copy()
      clean_df['high humadity label']=(clean_df['relative_humidity_3pm']>28)*1
      clean_df['high humadity label'].head()
[13]: 0
           1
      1
           0
      2
           0
      3
           0
           1
      Name: high humadity label, dtype: int32
[14]: #target variable
      y=clean_df[['high humadity label']].copy()
      y.head()
[14]:
         high humadity label
      0
                            1
      1
                           0
      2
                           0
                           0
      3
      4
                           1
[15]: df.columns
      features=['air_pressure_9am', 'air_temp_9am', 'avg_wind_direction_9am',
             'avg_wind_speed_9am', 'max_wind_direction_9am', 'max_wind_speed_9am',
             'rain_accumulation_9am', 'rain_duration_9am', 'relative_humidity_9am',
```

```
[16]: x=clean_df[features].copy()
      x.columns
[16]: Index(['air_pressure_9am', 'air_temp_9am', 'avg_wind_direction_9am',
             'avg wind speed 9am', 'max wind direction 9am', 'max wind speed 9am',
             'rain_accumulation_9am', 'rain_duration_9am', 'relative_humidity_9am'],
            dtype='object')
[17]: y.columns
[17]: Index(['high humadity label'], dtype='object')
[18]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
       \rightarrow33, random state=324)
[19]: humidity_classifier=DecisionTreeClassifier(max_leaf_nodes=10,random_state=0)
      humidity_classifier.fit(x_train,y_train)
[19]: DecisionTreeClassifier(max_leaf_nodes=10, random_state=0)
[20]: y_predicted=humidity_classifier.predict(x_test)
      y_predicted
[20]: array([0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0,
             1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0,
             0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0,
             0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0,
             0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1,
             1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0,
             1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1,
             0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1,
             0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1,
            0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1,
             1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1,
             0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0,
            0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0,
             0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0,
             0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0,
             1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0])
[21]: from sklearn.metrics import accuracy_score
      accuracy = accuracy_score(y_test, y_predicted) * 100
      print(f"Accuracy: {accuracy:.2f}%")
     Accuracy: 88.92%
[22]: confusion matrix(y test,y predicted)
```

plt.show()

