## Notebook

June 2, 2025

```
[5]: import pandas as pd
     import numpy as np
     from sklearn.model_selection import train_test_split
     from sklearn.preprocessing import StandardScaler
     from sklearn.ensemble import RandomForestClassifier
     from sklearn.metrics import classification_report, confusion_matrix, __
      ⇔accuracy_score
     import matplotlib.pyplot as plt
     import seaborn as sns
     # Step 1: Load and prepare the data
     def load_weather_data(data_string):
         # Create DataFrame
         df = pd.read_excel(data_string)
         # Convert columns to appropriate data types
         numeric cols = [
             'last_updated_epoch', 'temperature_celsius', 'temperature_fahrenheit',
             'wind_mph', 'wind_kph', 'wind_degree', 'pressure_mb', 'pressure_in',
             'precip_mm', 'precip_in', 'humidity', 'cloud', 'feels_like_celsius',
             'feels_like_fahrenheit', 'visibility_km', 'visibility_miles', u

    uv_index',

             'gust_mph', 'gust_kph'
         1
         for col in numeric_cols:
             if col in df.columns:
                 df[col] = pd.to_numeric(df[col], errors='coerce')
         # Convert timestamp to datetime
         if 'last_updated_epoch' in df.columns:
             df['datetime'] = pd.to_datetime(df['last_updated_epoch'], unit='s')
         return df
```

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# Sample data string - replace this with your actual data in production
data_string = r"C:\Users\arjun\Downloads\Weather data.xlsx\Weather data.xlsx"
# Load the data
weather_data = load_weather_data(data_string)
# Step 2: Define weather conditions based on available features
def determine_weather_condition(row):
   Determine weather condition based on available meteorological data
    - Rainy: any precipitation or very high humidity with high cloud cover
    - Cloudy: high cloud cover but no precipitation
    - Sunny: low cloud cover
    11 11 11
   if row['precip_mm'] > 0:
       return 0 # Rainy
   elif row['cloud'] > 70:
       return 1 # Cloudy
   else:
       return 2 # Sunny
# Add weather condition to dataset
weather_data['weather_condition'] = weather_data.
 ⇒apply(determine weather condition, axis=1)
# Add weather condition labels
weather_labels = {0: 'Rainy', 1: 'Cloudy', 2: 'Sunny'}
weather_data['weather_label'] = weather_data['weather_condition'].
 →map(weather_labels)
# Create target variable (next hour's weather)
weather data['next hour weather'] = weather data['weather condition'].shift(-1)
weather_data['next_hour_weather_label'] = weather_data['weather_label'].
 ⇒shift(-1)
# Drop the last row which has NaN in the target variable
weather_data = weather_data.dropna(subset=['next_hour_weather'])
# Display the first few rows of the dataset
print("Sample of the processed weather dataset:")
print(weather_data[['datetime', 'temperature_celsius', 'humidity', 'cloud',
                   'precip_mm', 'weather_label', 'next_hour_weather_label']].
 →head())
# Step 3: Feature Engineering
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# Extract time features
weather_data['hour'] = weather_data['datetime'].dt.hour
weather_data['day'] = weather_data['datetime'].dt.day
weather_data['month'] = weather_data['datetime'].dt.month
weather_data['day_of_week'] = weather_data['datetime'].dt.dayofweek
# Calculate differences from previous hour
weather_data['temp_diff'] = weather_data['temperature_celsius'].diff().fillna(0)
weather_data['humidity_diff'] = weather_data['humidity'].diff().fillna(0)
weather_data['pressure_diff'] = weather_data['pressure_mb'].diff().fillna(0)
weather_data['cloud_diff'] = weather_data['cloud'].diff().fillna(0)
# Calculate rolling averages (3-hour)
weather_data['temp 3h_avg'] = weather_data['temperature_celsius'].
 Grolling(window=3).mean().fillna(weather_data['temperature_celsius'])
weather_data['humidity_3h_avg'] = weather_data['humidity'].rolling(window=3).
 →mean().fillna(weather_data['humidity'])
weather_data['pressure_3h_avg'] = weather_data['pressure_mb'].rolling(window=3).

¬mean().fillna(weather_data['pressure_mb'])
weather_data['cloud_3h_avg'] = weather_data['cloud'].rolling(window=3).mean().

→fillna(weather_data['cloud'])
# Step 4: Exploratory Data Analysis
# Check distribution of target variable
print("\nDistribution of weather conditions:")
print(weather_data['next_hour_weather_label'].value_counts())
# Create visualizations
plt.figure(figsize=(10, 6))
sns.boxplot(x='weather_label', y='temperature_celsius', data=weather_data)
plt.title('Temperature Distribution by Weather Condition')
plt.savefig('temp_by_weather.png')
plt.close()
plt.figure(figsize=(10, 6))
sns.boxplot(x='weather_label', y='humidity', data=weather_data)
plt.title('Humidity Distribution by Weather Condition')
plt.savefig('humidity_by_weather.png')
plt.close()
plt.figure(figsize=(10, 6))
sns.boxplot(x='weather_label', y='cloud', data=weather_data)
plt.title('Cloud Cover Distribution by Weather Condition')
plt.savefig('cloud_by_weather.png')
plt.close()
# Create correlation matrix for numeric features
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plt.figure(figsize=(16, 12))
numeric_columns = ['temperature_celsius', 'humidity', 'pressure_mb', 'wind_mph',
                  'cloud', 'precip_mm', 'uv_index', 'gust_mph',
                  'weather_condition', 'next_hour_weather']
correlation_data = weather_data[numeric_columns].corr()
sns.heatmap(correlation_data, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix of Weather Features')
plt.tight_layout()
plt.savefig('correlation_matrix.png')
plt.close()
# Step 5: Prepare data for modeling
feature columns = [
    'temperature_celsius', 'humidity', 'pressure_mb', 'wind_mph', 'cloud',
    'precip_mm', 'visibility km', 'uv_index', 'gust_mph', 'weather_condition',
    'hour', 'day_of_week', 'month', 'temp_diff', 'humidity_diff', u
 'cloud_diff', 'temp_3h_avg', 'humidity_3h_avg', 'pressure_3h_avg',
]
X = weather_data[feature_columns]
y = weather_data['next_hour_weather']
# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,_
⇒random state=42)
# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
# Step 6: Train the model
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train_scaled, y_train)
# Step 7: Evaluate the model
y_pred = rf_model.predict(X_test_scaled)
# Calculate evaluation metrics
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred, target_names=['Rainy',_
print("\nModel Evaluation:")
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print(f"Accuracy: {accuracy:.4f}")
print("\nConfusion Matrix:")
print(conf_matrix)
print("\nClassification Report:")
print(class_report)
# Visualize confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Rainy', 'Cloudy', 'Sunny'],
            yticklabels=['Rainy', 'Cloudy', 'Sunny'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.tight_layout()
plt.savefig('confusion_matrix.png')
plt.close()
# Feature importance
feature_importance = pd.DataFrame({
    'Feature': feature_columns,
    'Importance': rf_model.feature_importances_
}).sort_values('Importance', ascending=False)
print("\nFeature Importance:")
print(feature importance.head(10)) # Show top 10 features
plt.figure(figsize=(12, 8))
sns.barplot(x='Importance', y='Feature', data=feature_importance.head(15))
plt.title('Top 15 Feature Importance')
plt.tight_layout()
plt.savefig('feature_importance.png')
plt.close()
# Step 8: Function to predict weather for new data
def predict_next_hour_weather(model, scaler, feature_values):
    Predict the next hour's weather based on current conditions
    Parameters:
    - model: trained classifier model
    - scaler: fitted StandardScaler
    - feature_values: dictionary of feature values matching the model's_{\sqcup}
 \hookrightarrow expected features
    Returns:
    - predicted weather condition as string ('Rainy', 'Cloudy', or 'Sunny')
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- probabilities for each class
    # Create a dataframe with the input features
    input_data = pd.DataFrame([feature_values])
    # Ensure all required features are present
    for col in feature columns:
        if col not in input_data.columns:
            input_data[col] = 0 # Set missing features to 0
    # Make sure columns are in the correct order
    input_data = input_data[feature_columns]
    # Scale the input data
    input_data_scaled = scaler.transform(input_data)
    # Make prediction
    prediction = model.predict(input_data_scaled)[0]
    probabilities = model.predict_proba(input_data_scaled)[0]
    # Convert numerical prediction to label
    weather_labels = {0: 'Rainy', 1: 'Cloudy', 2: 'Sunny'}
    predicted_weather = weather_labels[prediction]
    return predicted_weather, probabilities
# Example: Current weather data
example_weather = {
    'temperature_celsius': 28.5,
    'humidity': 65,
    'pressure_mb': 1008,
    'wind_mph': 12.0,
    'cloud': 30,
    'precip_mm': 0,
    'visibility_km': 10,
    'uv_index': 7,
    'gust_mph': 14.0,
    'weather_condition': 2, # Current: Sunny
    'hour': 14,
    'day_of_week': 3, # Thursday
    'month': 8, # August
    'temp_diff': 0.5,
    'humidity_diff': -2.0,
    'pressure_diff': -1.0,
    'cloud_diff': 5.0,
    'temp_3h_avg': 28.0,
    'humidity_3h_avg': 66.0,
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'pressure_3h_avg': 1008.5,
     'cloud_3h_avg': 28.0
}
predicted_weather, probabilities = predict_next_hour_weather(rf_model, scaler,_u
  ⇔example_weather)
print(f"\nPredicted weather for next hour: {predicted_weather}")
print(f"Prediction probabilities: Rainy: {probabilities[0]:.2f}, Cloudy:
  ⇔{probabilities[1]:.2f}, Sunny: {probabilities[2]:.2f}")
# Step 9: Save the model
import joblib
# Save the model and scaler
joblib.dump(rf_model, 'hourly_weather_model.pkl')
joblib.dump(scaler, 'hourly_weather_scaler.pkl')
print("\nModel and scaler saved successfully!")
Sample of the processed weather dataset:
             datetime temperature_celsius humidity cloud precip_mm \
0 2023-08-25 21:46:41
                                      27.5
                                                   67
                                                          26
                                                                    0.0
1 2023-08-25 21:46:42
                                      27.5
                                                   70
                                                          19
                                                                    0.0
2 2023-08-25 21:46:43
                                      26.3
                                                   70
                                                          51
                                                                    0.0
3 2023-08-25 21:46:44
                                      25.6
                                                   76
                                                          65
                                                                    0.0
4 2023-08-25 21:46:45
                                                          82
                                                                    0.0
                                      27.2
                                                   74
  weather_label next_hour_weather_label
0
          Sunny
                                  Sunny
1
          Sunny
                                  Sunny
2
          Sunny
                                  Sunny
3
          Sunny
                                 Cloudy
4
         Cloudy
                                  Sunny
Distribution of weather conditions:
next_hour_weather_label
Sunny
          14479
Rainy
           7354
           2236
Cloudy
Name: count, dtype: int64
Model Evaluation:
Accuracy: 0.6961
Confusion Matrix:
[[ 765
         28 627]
```

```
[ 168 54 221]
[ 398 21 2532]]
```

## Classification Report:

support	f1-score	recall	precision	
1420	0.56	0.54	0.57	Rainy
443	0.20	0.12	0.52	Cloudy
2951	0.80	0.86	0.75	Sunny
4814	0.70			accuracy
4814	0.52	0.51	0.62	macro avg
4814	0.67	0.70	0.68	weighted avg

## Feature Importance:

	Feature	Importance
20	cloud_3h_avg	0.117155
4	cloud	0.084957
18	humidity_3h_avg	0.084219
17	temp_3h_avg	0.064452
16	cloud_diff	0.064283
8	${ t gust\_mph}$	0.060353
13	${\tt temp\_diff}$	0.058491
0	temperature_celsius	0.057158
1	humidity	0.053519
14	humidity_diff	0.052484

Predicted weather for next hour: Sunny

Prediction probabilities: Rainy: 0.10, Cloudy: 0.02, Sunny: 0.88

Model and scaler saved successfully!

```
[7]: def interactive_hourly_prediction():
    """
    Interactive function to input current weather data and predict next hour's
    weather
    """
    print("\n===== Hourly Weather Prediction Tool =====")
    print("Enter current weather data to predict weather for the next hour")

# Get user input for key weather metrics
    temp = float(input("Current temperature (°C): "))
    humidity = float(input("Current humidity (%): "))
    pressure = float(input("Current pressure (mb): "))
    wind = float(input("Current wind speed (mph): "))
    cloud = float(input("Current cloud cover (0-100%): "))
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precip = float(input("Current precipitation (mm): "))
  # Set up the prediction input
  current_hour = int(input("Current hour of day (0-23): "))
  current_day = int(input("Current day of week (0=Monday, 6=Sunday): "))
  current_month = int(input("Current month (1-12): "))
  # Determine current weather condition
  if precip > 0:
      current_condition = 0 # Rainy
  elif cloud > 70:
      current_condition = 1 # Cloudy
  else:
      current_condition = 2 # Sunny
  # Create prediction input
  prediction_input = {
      'temperature_celsius': temp,
      'humidity': humidity,
      'pressure_mb': pressure,
      'wind_mph': wind,
      'cloud': cloud,
      'precip_mm': precip,
      'visibility km': 10, # Default value
      'uv_index': 5, # Default value
      'gust mph': wind * 1.2, # Estimate qust as 20% higher than wind speed
      'weather_condition': current_condition,
      'hour': current_hour,
      'day_of_week': current_day,
      'month': current_month,
      'temp_diff': 0, # Assuming we don't have previous data
      'humidity_diff': 0,
      'pressure_diff': 0,
      'cloud_diff': 0,
      'temp_3h_avg': temp, # Using current values as approximation
      'humidity_3h_avg': humidity,
      'pressure_3h_avg': pressure,
      'cloud_3h_avg': cloud
  }
  # Load the model and make prediction
  loaded_model = joblib.load('hourly_weather_model.pkl')
  loaded_scaler = joblib.load('hourly_weather_scaler.pkl')
  prediction, probs = predict_next_hour_weather(loaded_model, loaded_scaler,_
→prediction_input)
```

```
# Display results
    print("\n===== Prediction Results =====")
    print(f"Weather for the next hour is predicted to be: {prediction}")
    print(f"Prediction confidence:")
    print(f" Rainy: {probs[0]:.2f} ({probs[0]*100:.1f}%)")
    print(f" Cloudy: {probs[1]:.2f} ({probs[1]*100:.1f}%)")
    print(f" Sunny: {probs[2]:.2f} ({probs[2]*100:.1f}%)")
    if max(probs) < 0.5:</pre>
        print("\nNote: This prediction has low confidence.")
# Uncomment to use the interactive prediction tool
interactive_hourly_prediction()
==== Hourly Weather Prediction Tool =====
Enter current weather data to predict weather for the next hour
Current temperature (°C): 29
Current humidity (%): 94
Current pressure (mb): 29.74
Current wind speed (mph): 12
Current cloud cover (0-100%): 71
Current precipitation (mm): 0.00
Current hour of day (0-23): 9
Current day of week (0=Monday, 6=Sunday): 6
Current month (1-12): 5
===== Prediction Results =====
Weather for the next hour is predicted to be: Sunny
Prediction confidence:
  Rainy: 0.34 (34.0%)
 Cloudy: 0.24 (24.0%)
```

Note: This prediction has low confidence.

Sunny: 0.42 (42.0%)

[]:

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