Task_01 : Weather Forecasting

Team: Cyferlink

[3]:

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

Dataset View

[13]:

```python
df = pd.read_csv(r"C:\Users\Gaya\Downloads\weather_data.csv")
df.head()
```

[13]:

	date	avg_temperature	humidity	avg_wind_speed	rain_or_not	cloud_cover	pressure
0	2023-01-01	23.745401	46.140905	7.845981	Rain	20.851051	992.965681
1	2023-01-02	30.030503	59.876587	5.382457	Rain	93.059521	1037.273025
2	2023-01-03	28.365224	51.464618	13.158008	Rain	11.636640	1034.193357
3	2023-01-04	27.550929	53.103799	5.886677	Rain	81.744971	968.610142
4	2023-01-05	23.639303	57.826186	12.248992	Rain	38.062329	1030.264331

Data Preparation

[3]:

```python
from sklearn.preprocessing import  StandardScaler
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.pipeline import Pipeline
```

[4]:

```python
df.describe()
```

[4]:

	avg_temperature	humidity	avg_wind_speed	cloud_cover	pressure
count	296.000000	296.000000	296.000000	296.000000	311.000000
mean	25.983840	55.041385	7.556636	49.834827	1001.059119
std	6.802475	19.220133	5.344683	29.009459	28.835595
min	15.000000	30.000000	0.069480	0.321826	951.240404
25%	20.265692	34.280826	3.550354	24.530951	975.757545
50%	27.177958	56.759806	7.326421	50.725120	1001.938586
75%	32.204599	72.189837	11.050627	76.046506	1026.578884
max	35.000000	90.000000	56.636041	99.834751	1049.543752

Data types

[15]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 311 entries, 0 to 310
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   date             311 non-null    object
 1   avg_temperature  296 non-null    float64
 2   humidity         296 non-null    float64
 3   avg_wind_speed   296 non-null    float64
 4   rain_or_not      311 non-null    object
 5   cloud_cover      296 non-null    float64
 6   pressure         311 non-null    float64
dtypes: float64(5), object(2)
memory usage: 17.1+ KB
```

Check Missing Values

[17]:
```
df.isna().sum()
```

[17]:
```
date                0
avg_temperature    15
humidity           15
avg_wind_speed     15
rain_or_not         0
cloud_cover        15
pressure            0
dtype: int64
```

[19]:

```
df_processed = df.copy()
```

Data pre-processing Pipeline

[104]:

```
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
import pandas as pd

class NumericConverter(BaseEstimator, TransformerMixin):
    def fit(self, data, target=None):
        return self

    def transform(self, data):
        numeric_columns = ['avg_temperature', 'humidity', 'avg_wind_speed', 'cloud_cover', 'pressure']
        data[numeric_columns] = data[numeric_columns].apply(pd.to_numeric, errors='coerce')
        return data

features_to_scale = ['avg_temperature', 'humidity', 'avg_wind_speed', 'cloud_cover', 'pressure']

class MissingValueHandler(BaseEstimator, TransformerMixin):
    def fit(self, data, target=None):
        return self

    def transform(self, data):
        for feature in features_to_scale:
            data[feature].fillna(data[feature].median(), inplace=True)
        return data

class DataStandardizer(BaseEstimator, TransformerMixin):
    def fit(self, data, target=None):
        self.scaler = StandardScaler()
        self.scaler.fit(data[features_to_scale])  # Fit on training data
        return self

    def transform(self, data):
        data[features_to_scale] = self.scaler.transform(data[features_to_scale])  # Apply same scaler
        return data

class TargetEncoder(BaseEstimator, TransformerMixin):
    def fit(self, data, target=None):
        return self

    def transform(self, data):
        data['rain_or_not'] = (data['rain_or_not'] == "Rain").astype(int)
        return data

class FeatureEncoder(BaseEstimator, TransformerMixin):
    def fit(self, data, target=None):
        return self

    def transform(self, data):
        data['date'] = pd.to_datetime(data['date'], errors='coerce')
        data['month'] = data['date'].dt.month.astype(str)
        data['day'] = data['date'].dt.day.astype(str)
        return data.drop(columns=['date'])

data_preprocessing_pipeline = Pipeline(steps=[
    ('NumericConversion', NumericConverter()),
    ('HandleMissingValues', MissingValueHandler()),
    ('StandardizeFeatures', DataStandardizer()),
    ('EncodeFeatures', FeatureEncoder()),
    ('EncodeTarget', TargetEncoder())
])
```

[106]:
```
df_processed = data_preprocessing_pipeline.fit_transform(df)
```

```
C:\Users\Gaya\AppData\Local\Temp\ipykernel_11148\1734546371.py:23: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through
chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behave
s as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) inst
ead, to perform the operation inplace on the original object.


  data[feature].fillna(data[feature].median(), inplace=True)
```

[57]:
```
df_processed.head()
```

[57]:

	avg_temperature	humidity	avg_wind_speed	rain_or_not	cloud_cover	pressure	month	day
0	-0.346303	-0.479808	0.057716	1	-1.027348	-0.281128	1	1
1	0.601659	0.253825	-0.415527	1	1.528340	1.257899	1	2
2	0.350490	-0.195465	1.078158	1	-1.353475	1.150926	1	3
3	0.227672	-0.107915	-0.318667	1	1.127882	-1.127123	1	4
4	-0.362306	0.144312	0.903535	1	-0.418186	1.014450	1	5

[108]:
```
df_processed.isna().sum()
```

[108]:
```
avg_temperature    0
humidity           0
avg_wind_speed     0
rain_or_not        0
cloud_cover        0
pressure           0
month              0
day                0
dtype: int64
```

[65]:
```
df_processed.describe()
```

[65]:

	avg_temperature	humidity	avg_wind_speed	rain_or_not	cloud_cover	pressure
count	3.110000e+02	3.110000e+02	3.110000e+02	311.000000	3.110000e+02	3.110000e+02
mean	1.028116e-16	4.569407e-16	7.425286e-17	0.636656	-2.855879e-17	8.674733e-16
std	1.001612e+00	1.001612e+00	1.001612e+00	0.481738	1.001612e+00	1.001612e+00
min	-1.665345e+00	-1.341906e+00	-1.436151e+00	0.000000	-1.753943e+00	-1.730466e+00
25%	-8.367950e-01	-1.038202e+00	-7.364830e-01	0.000000	-8.466853e-01	-8.788565e-01
50%	1.714184e-01	8.735538e-02	-4.209132e-02	1.000000	2.999052e-02	3.054851e-02
75%	8.773980e-01	9.001727e-01	6.438495e-01	1.000000	8.595001e-01	8.864354e-01
max	1.351192e+00	1.862740e+00	9.430295e+00	1.000000	1.768137e+00	1.684126e+00

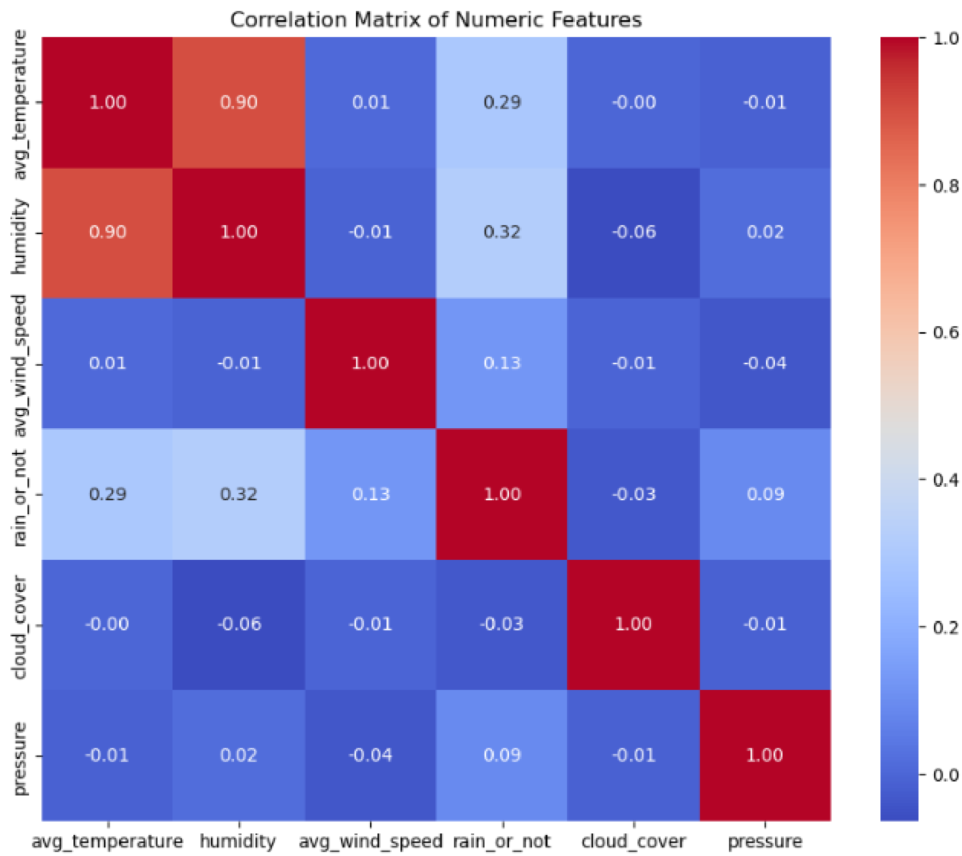
Exploratory Data Analysis

[110]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

Correlation Analysis (Heatmap)

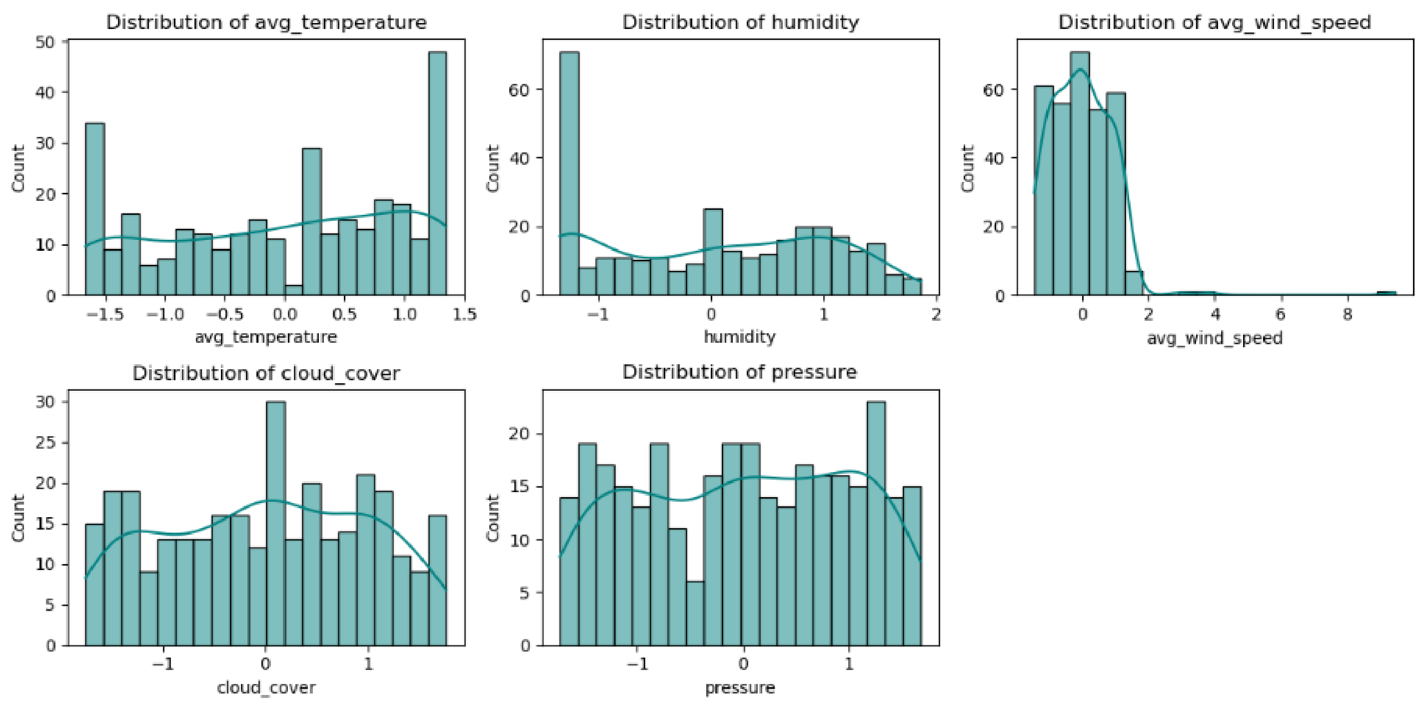
[114]:

```python
# Drop 'day' and 'month' columns to focus on numeric features
df_numeric = df_processed.drop(['day', 'month'], axis=1)

# Calculate the correlation matrix
correlation_matrix = df_numeric.corr()

# Plot the correlation matrix as a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix of Numeric Features')
plt.savefig("correlation_matrix.png")
plt.show()
```



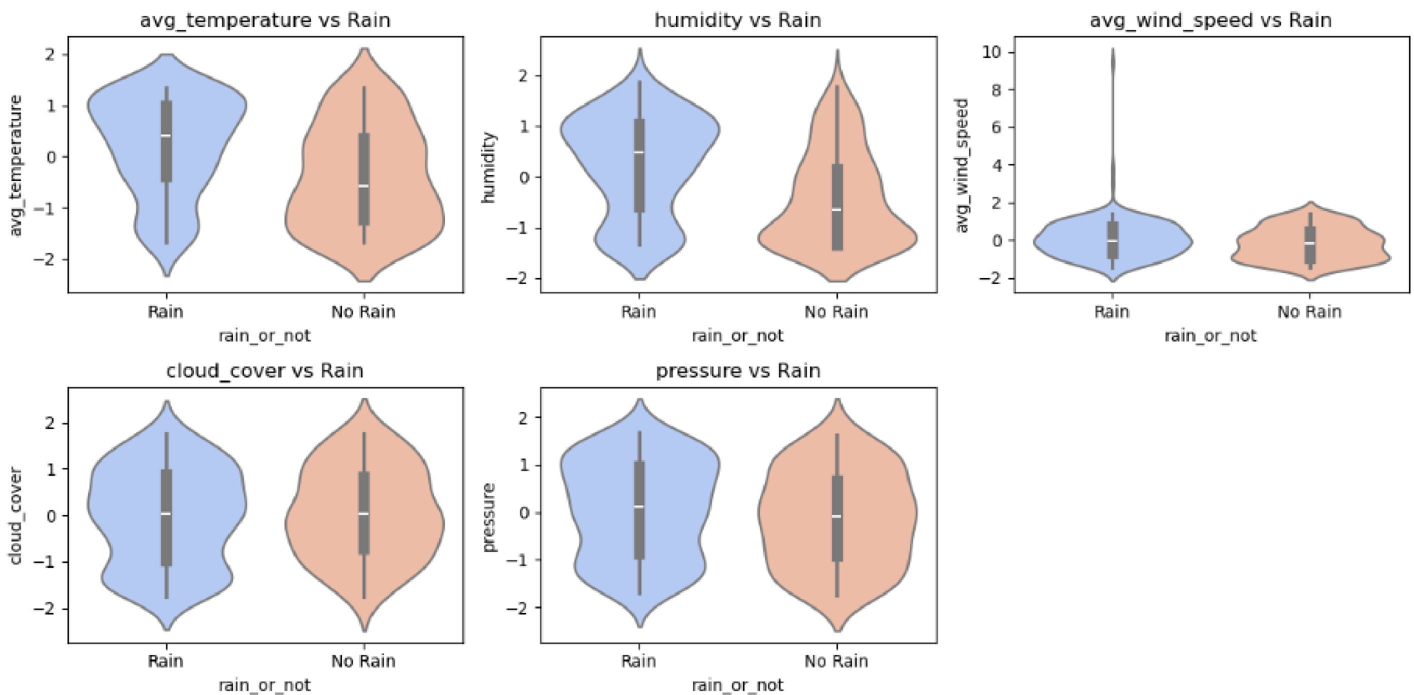
Feature Distributions (Histograms & KDE Plots)

[120]:
```
# Define the features to visualize
selected_features = ['avg_temperature', 'humidity', 'avg_wind_speed', 'cloud_cover', 'pressure']

# Create subplots for histograms of each feature
plt.figure(figsize=(12, 6))
for index, feature in enumerate(selected_features):
    plt.subplot(2, 3, index + 1)
    sns.histplot(df[feature], kde=True, bins=20, color='teal', edgecolor='black')  # Customized color
    plt.title(f'Distribution of {feature}')
plt.tight_layout()
plt.show()
```



Rain Probability by Feature (Violin & Boxplots)

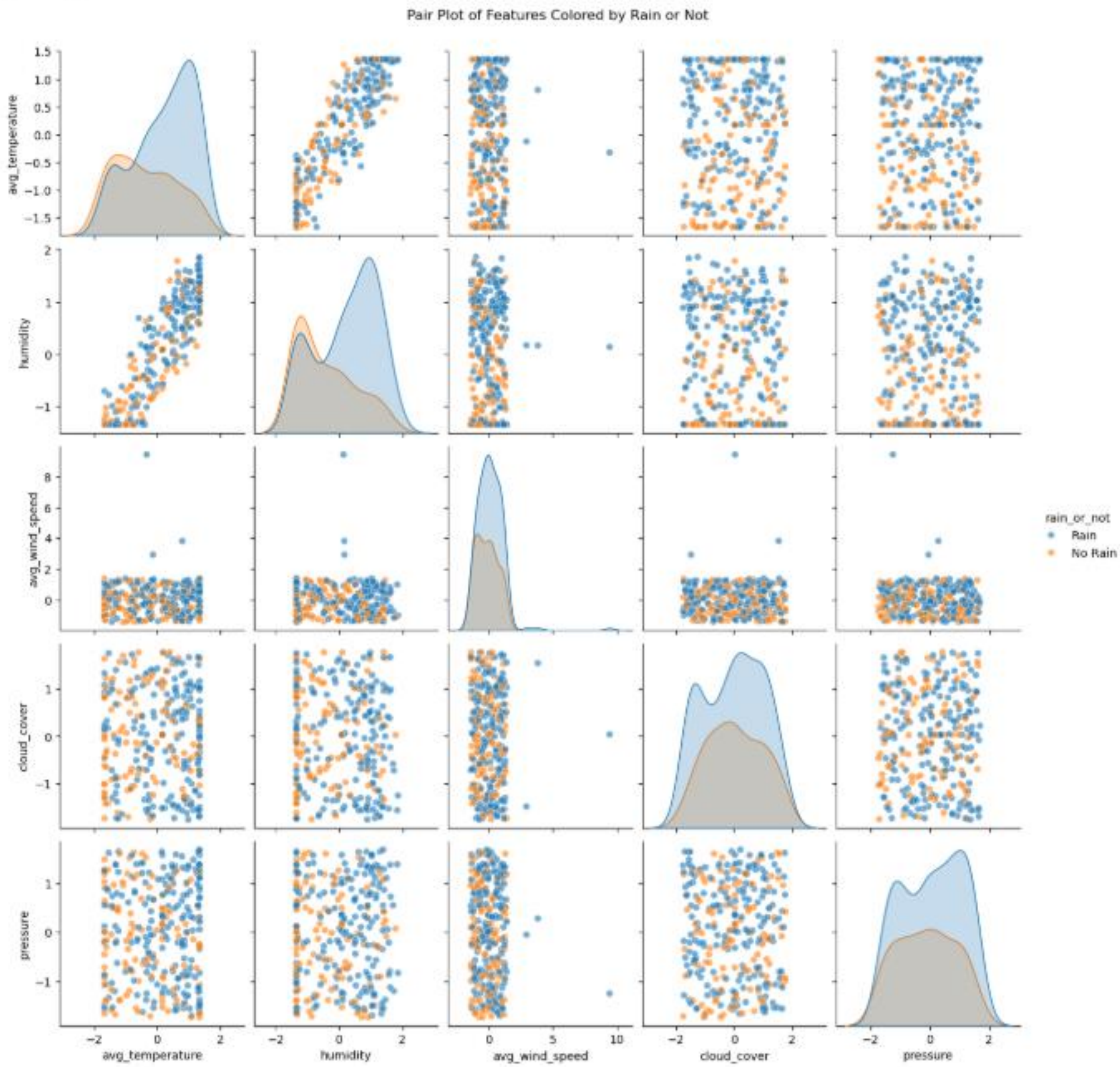
[128]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Define the features to visualize
selected_features = ['avg_temperature', 'humidity', 'avg_wind_speed', 'cloud_cover', 'pressure']

# Create subplots for violin plots of each feature
plt.figure(figsize=(12, 6))
for index, feature in enumerate(selected_features):
    plt.subplot(2, 3, index + 1)
    sns.violinplot(x=df['rain_or_not'], y=df[feature], hue=df['rain_or_not'], palette='coolwarm', linewidth=1.5, legend=False)  # Updated to use `hue`
    plt.title(f'{feature} vs Rain')
plt.tight_layout()
plt.savefig('rain_probability_vs_features.png')  # Save the plot
plt.show()
```



Pairplots (Feature Interactions)

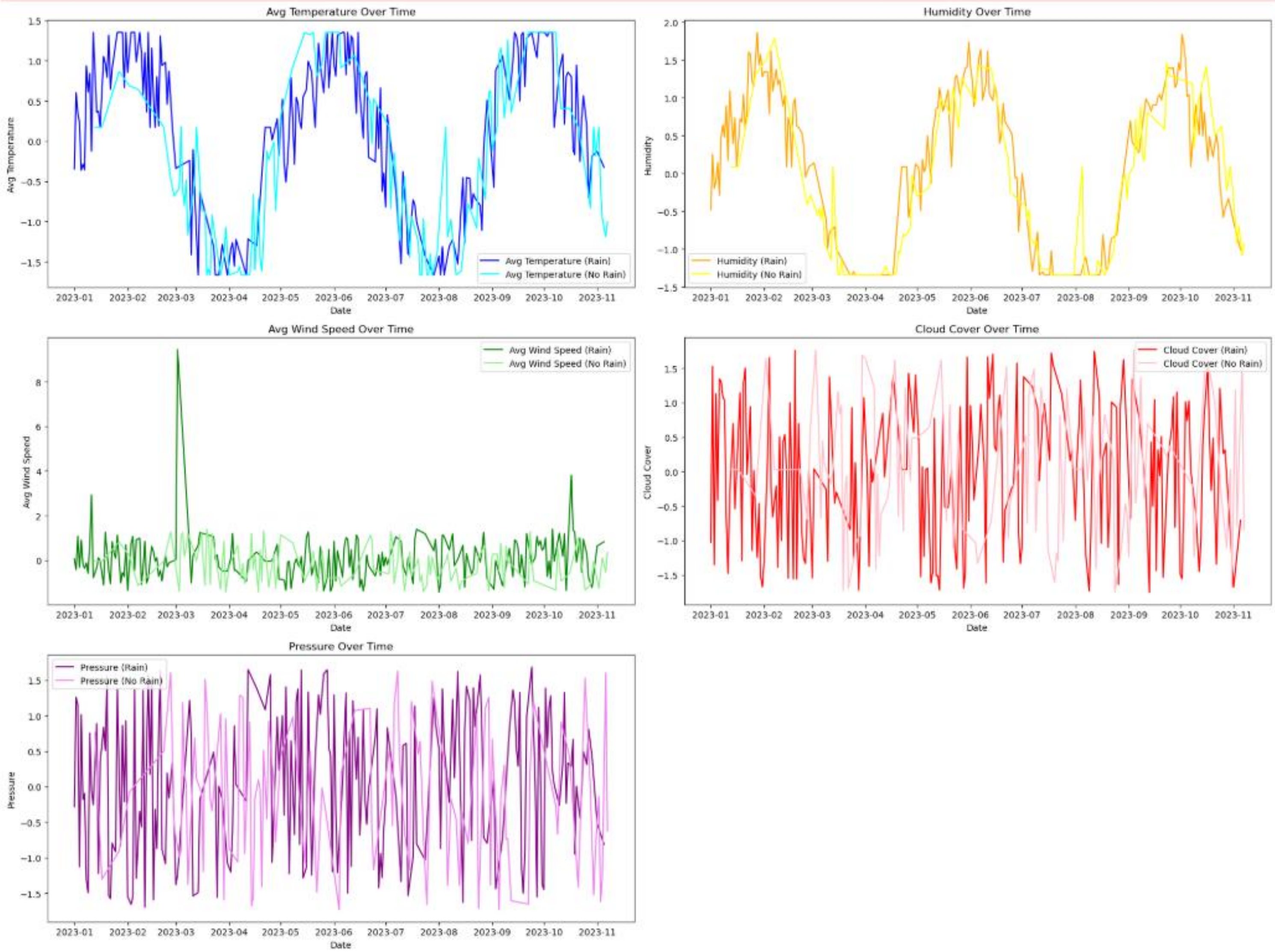
[132]:

```python
import seaborn as sns
import matplotlib.pyplot as plt

# Create a pair plot with hue for 'rain_or_not' and KDE on the diagonal
sns.pairplot(df, hue="rain_or_not", diag_kind="kde", plot_kws={'alpha': 0.6})

# Add a title to the plot
plt.suptitle('Pair Plot of Features Colored by Rain or Not', y=1.02)

# Save the plot
plt.savefig('pair_plot_rain_or_not.png', bbox_inches='tight')

# Display the plot
plt.show()
```



[144]:
```python
# Define the preprocessing pipeline
data_preprocessing_pipeline_2 = Pipeline(steps=[
    ('TypeCastToNum', ConvertToNum()),
    ('Missingval', Missingval()),
    ('StandardizeData', StandardizeData()),
    ('DataEncoder', DataEncoder()),  # Ensure this does not drop the 'date' column
    ('TargetEncode', TargetEncode())
])

# Apply the pipeline to the data
df_with_date = df.copy()
df_with_date = data_preprocessing_pipeline_2.fit_transform(df_with_date)

# Ensure the 'date' column is preserved for plotting
if 'date' not in df_with_date.columns:
    df_with_date['date'] = df['date']  # Add the 'date' column back if it was dropped

# Plot time series data for different features
plt.figure(figsize=(20, 15))

# Plot avg_temperature over time
plt.subplot(3, 2, 1)
plt.plot(df_with_date[df_with_date['rain_or_not'] == 1]['date'], df_with_date[df_with_date['rain_or_not'] == 1]['avg_temperature'], label='Avg Temperat
plt.plot(df_with_date[df_with_date['rain_or_not'] == 0]['date'], df_with_date[df_with_date['rain_or_not'] == 0]['avg_temperature'], label='Avg Temperat
plt.xlabel('Date')
plt.ylabel('Avg Temperature')
plt.title('Avg Temperature Over Time')
plt.legend()

# Plot humidity over time
plt.subplot(3, 2, 2)
plt.plot(df_with_date[df_with_date['rain_or_not'] == 1]['date'], df_with_date[df_with_date['rain_or_not'] == 1]['humidity'], label='Humidity (Rain)', c
plt.plot(df_with_date[df_with_date['rain_or_not'] == 0]['date'], df_with_date[df_with_date['rain_or_not'] == 0]['humidity'], label='Humidity (No Rain)'
plt.xlabel('Date')
plt.ylabel('Humidity')
plt.title('Humidity Over Time')
plt.legend()

# Plot avg_wind_speed over time
plt.subplot(3, 2, 3)
plt.plot(df_with_date[df_with_date['rain_or_not'] == 1]['date'], df_with_date[df_with_date['rain_or_not'] == 1]['avg_wind_speed'], label='Avg Wind Spee
plt.plot(df_with_date[df_with_date['rain_or_not'] == 0]['date'], df_with_date[df_with_date['rain_or_not'] == 0]['avg_wind_speed'], label='Avg Wind Spee
plt.xlabel('Date')
plt.ylabel('Avg Wind Speed')
plt.title('Avg Wind Speed Over Time')
plt.legend()

# Plot cloud_cover over time
plt.subplot(3, 2, 4)
plt.plot(df_with_date[df_with_date['rain_or_not'] == 1]['date'], df_with_date[df_with_date['rain_or_not'] == 1]['cloud_cover'], label='Cloud Cover (Rai
plt.plot(df_with_date[df_with_date['rain_or_not'] == 0]['date'], df_with_date[df_with_date['rain_or_not'] == 0]['cloud_cover'], label='Cloud Cover (No
plt.xlabel('Date')
plt.ylabel('Cloud Cover')
plt.title('Cloud Cover Over Time')
plt.legend()

# Plot pressure over time
plt.subplot(3, 2, 5)
plt.plot(df_with_date[df_with_date['rain_or_not'] == 1]['date'], df_with_date[df_with_date['rain_or_not'] == 1]['pressure'], label='Pressure (Rain)', c
plt.plot(df_with_date[df_with_date['rain_or_not'] == 0]['date'], df_with_date[df_with_date['rain_or_not'] == 0]['pressure'], label='Pressure (No Rain)'
plt.xlabel('Date')
plt.ylabel('Pressure')
plt.title('Pressure Over Time')
plt.legend()

# Adjust layout and save the plot
plt.tight_layout()
plt.savefig('time_series_data.png')  # Save the plot
plt.show()
```

```
C:\Users\Gaya\AppData\Local\Temp\ipykernel_11148\2336740090.py:23: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.


  X[col].fillna(X[col].median(), inplace=True)
```



[85]:
```
df_with_date.head()
```

[85]:

	date	avg_temperature	humidity	avg_wind_speed	rain_or_not	cloud_cover	pressure	month	day
0	2023-01-01	-0.346303	-0.479808	0.057716	1	-1.027348	-0.281128	1	1
1	2023-01-02	0.601659	0.253825	-0.415527	1	1.528340	1.257899	1	2
2	2023-01-03	0.350490	-0.195465	1.078158	1	-1.353475	1.150926	1	3
3	2023-01-04	0.227672	-0.107915	-0.318667	1	1.127882	-1.127123	1	4
4	2023-01-05	-0.362306	0.144312	0.903535	1	-0.418186	1.014450	1	5

[86]:
```
df_processed.head()
```

[86]:

	avg_temperature	humidity	avg_wind_speed	rain_or_not	cloud_cover	pressure	month	day
0	-0.346303	-0.479808	0.057716	1	-1.027348	-0.281128	1	1
1	0.601659	0.253825	-0.415527	1	1.528340	1.257899	1	2
2	0.350490	-0.195465	1.078158	1	-1.353475	1.150926	1	3
3	0.227672	-0.107915	-0.318667	1	1.127882	-1.127123	1	4
4	-0.362306	0.144312	0.903535	1	-0.418186	1.014450	1	5

Model Building and Training

[142]:
```
# Drop 'month' and 'day' columns
df_processed_final = df_processed.drop(['month', 'day'], axis=1)

# Filter rows based on the 95th percentile of specific columns
df_processed_final = df_processed_final[
    (df_processed_final['avg_wind_speed'] < df_processed_final['avg_wind_speed'].quantile(0.95)) &
    (df_processed_final['avg_temperature'] < df_processed_final['avg_temperature'].quantile(0.95)) &
    (df_processed_final['humidity'] < df_processed_final['humidity'].quantile(0.95))
]

# Add a new 'dew_point' column
df_processed_final['dew_point'] = df_processed_final['avg_temperature'] - ((100 - df_processed_final['humidity']) / 5)

# Display the shape of the final DataFrame
print("Shape of the final DataFrame:", df_processed_final.shape)
```

```
Shape of the final DataFrame: (256, 7)
```

[146]:
```
df_processed_final.head()
```

[146]:

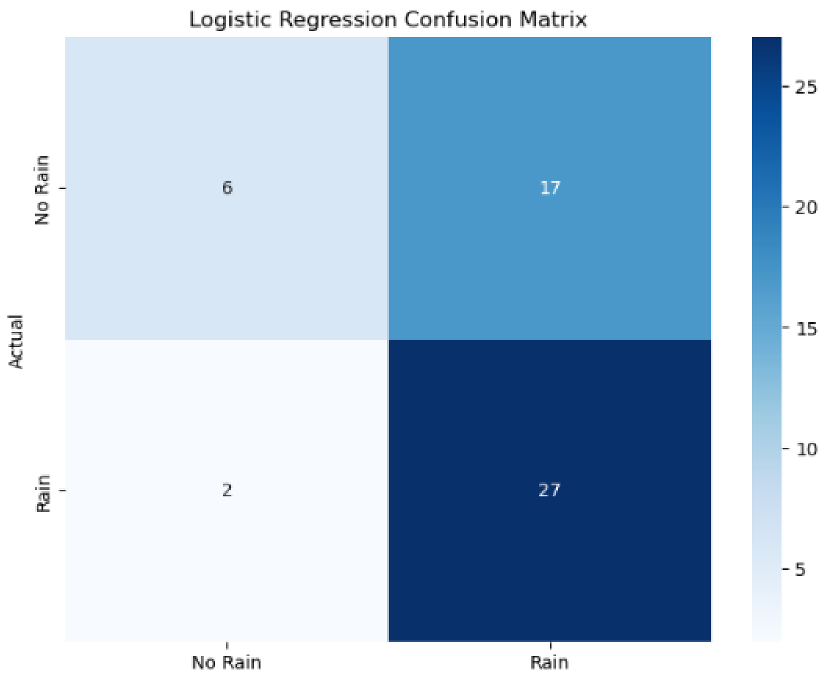
	avg_temperature	humidity	avg_wind_speed	rain_or_not	cloud_cover	pressure	dew_point
0	-0.346303	-0.479808	0.057716	1	-1.027348	-0.281128	-20.442265
1	0.601659	0.253825	-0.415527	1	1.528340	1.257899	-19.347576
2	0.350490	-0.195465	1.078158	1	-1.353475	1.150926	-19.688603
3	0.227672	-0.107915	-0.318667	1	1.127882	-1.127123	-19.793910
4	-0.362306	0.144312	0.903535	1	-0.418186	1.014450	-20.333443

```python
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, f1_score
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, AdaBoostClassifier, BaggingClassifier, ExtraTreesClassifier, VotingClas
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
import seaborn as sns
import matplotlib.pyplot as plt

# Prepare features and target
X = df_processed_final.drop('rain_or_not', axis=1)
y = df_processed_final['rain_or_not']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=32)

# Define models and their parameter grids
models = [
    ('Logistic Regression', LogisticRegression()),
    ('Random Forest', RandomForestClassifier()),
    ('SVM', SVC(probability=True)),  # Enable probability for VotingClassifier
    ('Decision Tree', DecisionTreeClassifier()),
    ('KNN', KNeighborsClassifier()),
    ('Naive Bayes', GaussianNB()),
    ('Gradient Boosting', GradientBoostingClassifier()),
    ('AdaBoost', AdaBoostClassifier()),
    ('Bagging', BaggingClassifier()),
    ('Extra Trees', ExtraTreesClassifier())
]

param_grid = {
    'Logistic Regression': {'C': [0.1, 1, 10]},
    'Random Forest': {'n_estimators': [50, 100, 200]},
    'SVM': {'C': [0.1, 1, 10], 'kernel': ['linear', 'rbf']},
    'Decision Tree': {'max_depth': [None, 10, 20]},
    'KNN': {'n_neighbors': [3, 5, 7]},
    'Naive Bayes': {},
    'Gradient Boosting': {'n_estimators': [50, 100, 200]},
    'AdaBoost': {'n_estimators': [50, 100, 200]},
    'Bagging': {'n_estimators': [50, 100, 200]},
    'Extra Trees': {'n_estimators': [50, 100, 200]}
}
```

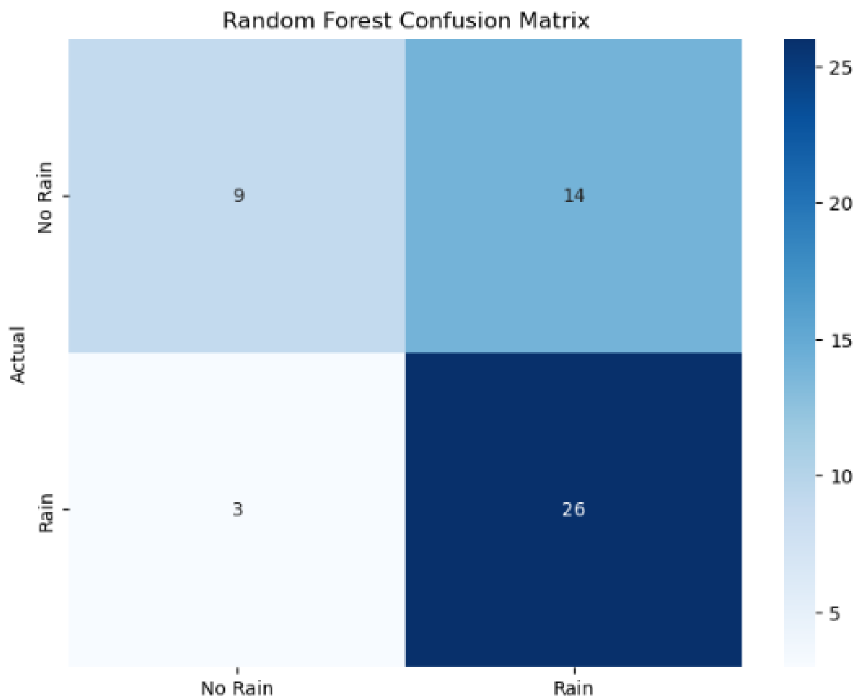
```python
param_grid = {
    'Logistic Regression': {'C': [0.1, 1, 10]},
    'Random Forest': {'n_estimators': [50, 100, 200]},
    'SVM': {'C': [0.1, 1, 10], 'kernel': ['linear', 'rbf']},
    'Decision Tree': {'max_depth': [None, 10, 20]},
    'KNN': {'n_neighbors': [3, 5, 7]},
    'Naive Bayes': {},
    'Gradient Boosting': {'n_estimators': [50, 100, 200]},
    'AdaBoost': {'n_estimators': [50, 100, 200]},
    'Bagging': {'n_estimators': [50, 100, 200]},
    'Extra Trees': {'n_estimators': [50, 100, 200]}
}

# Train and evaluate models
best_models = {}
high_accuracy_models = []

for name, model in models:
    print(f'Training and evaluating {name}...')
    grid_search = GridSearchCV(model, param_grid[name], cv=5, scoring='f1')
    grid_search.fit(X_train, y_train)
    best_models[name] = grid_search.best_estimator_

    # Evaluate on the test set
    y_pred = best_models[name].predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)

    print(f'{name} Best Params: {grid_search.best_params_}')
    print(f'{name} F1 Score: {f1}')
    print(f'{name} Accuracy: {accuracy}')
    print(f'{name} Classification Report: \n{classification_report(y_test, y_pred)}')

    # Add to high-accuracy models if accuracy > 0.6
    if accuracy > 0.6:
        high_accuracy_models.append(name)

    # Plot confusion matrix
    con_matrix = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(con_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['No Rain', 'Rain'], yticklabels=['No Rain', 'Rain'])
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title(f'{name} Confusion Matrix')
    plt.show()
```

```python
# Create a Voting Classifier with high-accuracy models
if high_accuracy_models:
    voting_estimators = [(name, best_models[name]) for name in high_accuracy_models]
    voting_clf = VotingClassifier(estimators=voting_estimators, voting='hard')

    # Train and evaluate the Voting Classifier
    voting_clf.fit(X_train, y_train)
    y_pred = voting_clf.predict(X_test)
    print(f'Voting Classifier F1 Score: {f1_score(y_test, y_pred)}')
    print(f'Voting Classifier Accuracy: {accuracy_score(y_test, y_pred)}')
    print(f'Voting Classifier Classification Report: \n{classification_report(y_test, y_pred)}')

    # Plot confusion matrix for Voting Classifier
    con_matrix = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(con_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['No Rain', 'Rain'], yticklabels=['No Rain', 'Rain'])
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title('Voting Classifier Confusion Matrix')
    plt.show()
else:
    print("No high-accuracy models found for Voting Classifier.")

# Print high-accuracy models
print("High-Accuracy Models:", high_accuracy_models)
```

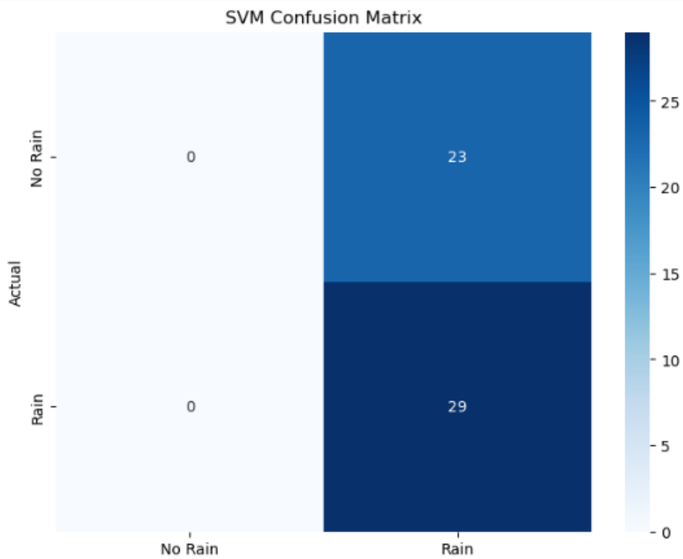
```
Training and evaluating Logistic Regression...
Logistic Regression Best Params: {'C': 0.1}
Logistic Regression F1 Score: 0.7397260273972602
Logistic Regression Accuracy: 0.6346153846153846
Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       0.75      0.26      0.39        23
           1       0.61      0.93      0.74        29

    accuracy                           0.63        52
   macro avg       0.68      0.60      0.56        52
weighted avg       0.67      0.63      0.58        52
```



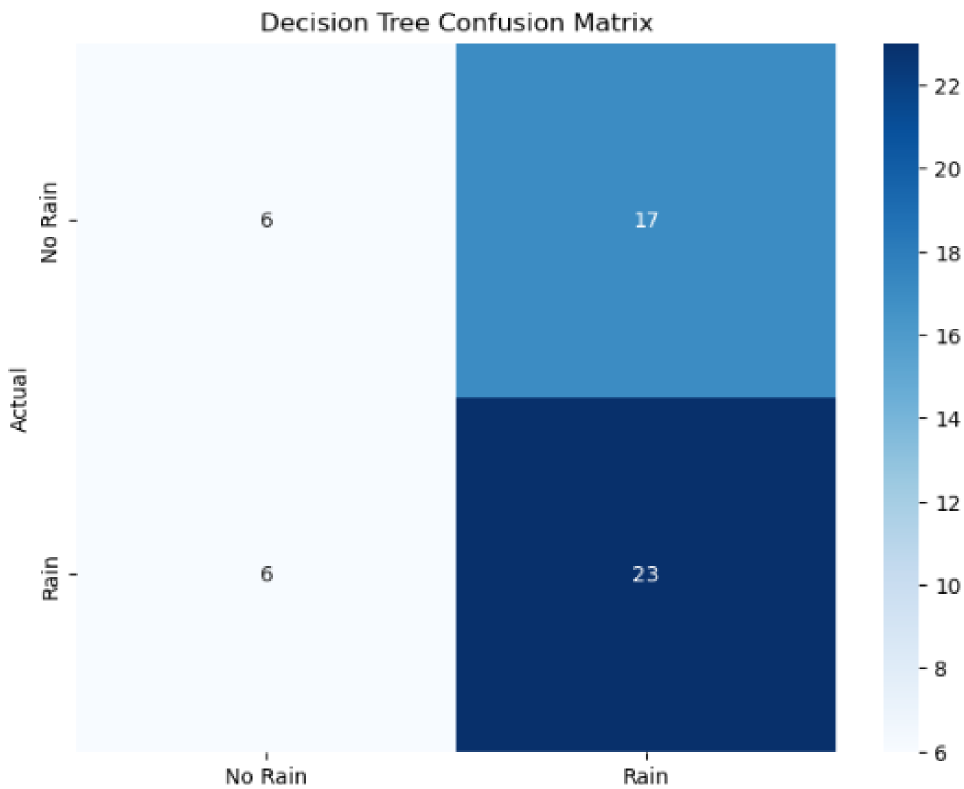
```
Training and evaluating Random Forest...
Random Forest Best Params: {'n_estimators': 200}
Random Forest F1 Score: 0.7536231884057971
Random Forest Accuracy: 0.6730769230769231
Random Forest Classification Report:
              precision    recall  f1-score   support

           0       0.75      0.39      0.51        23
           1       0.65      0.90      0.75        29

    accuracy                           0.67        52
   macro avg       0.70      0.64      0.63        52
weighted avg       0.69      0.67      0.65        52
```



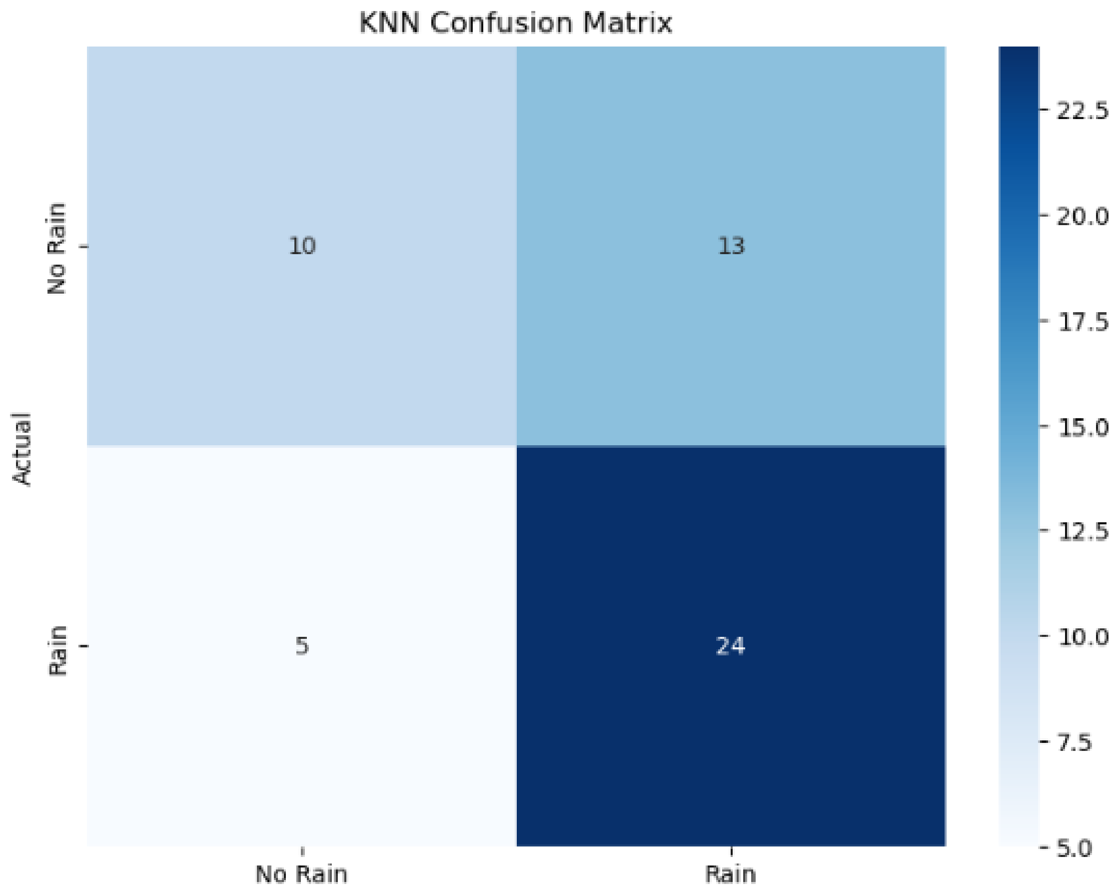
```
Training and evaluating SVM...
SVM Best Params: {'C': 0.1, 'kernel': 'rbf'}
SVM F1 Score: 0.7160493827160493
SVM Accuracy: 0.5576923076923077
SVM Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        23
           1       0.56      1.00      0.72        29

    accuracy                           0.56        52
   macro avg       0.28      0.50      0.36        52
weighted avg       0.31      0.56      0.40        52

C:\Users\Gaya\anaconda3\Lib\site-packages\sklearn\metrics\_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\Gaya\anaconda3\Lib\site-packages\sklearn\metrics\_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\Gaya\anaconda3\Lib\site-packages\sklearn\metrics\_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0
in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```



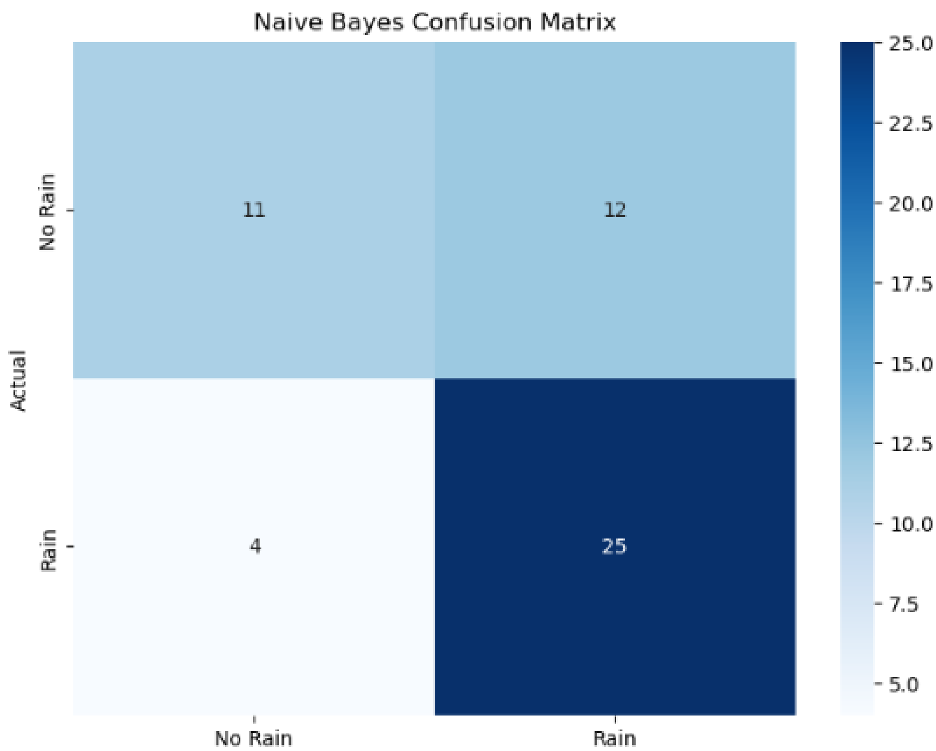
```
Training and evaluating Decision Tree...
Decision Tree Best Params: {'max_depth': 20}
Decision Tree F1 Score: 0.6666666666666666
Decision Tree Accuracy: 0.5576923076923077
Decision Tree Classification Report:
              precision    recall  f1-score   support

           0       0.50      0.26      0.34        23
           1       0.57      0.79      0.67        29

    accuracy                           0.56        52
   macro avg       0.54      0.53      0.50        52
weighted avg       0.54      0.56      0.52        52
```



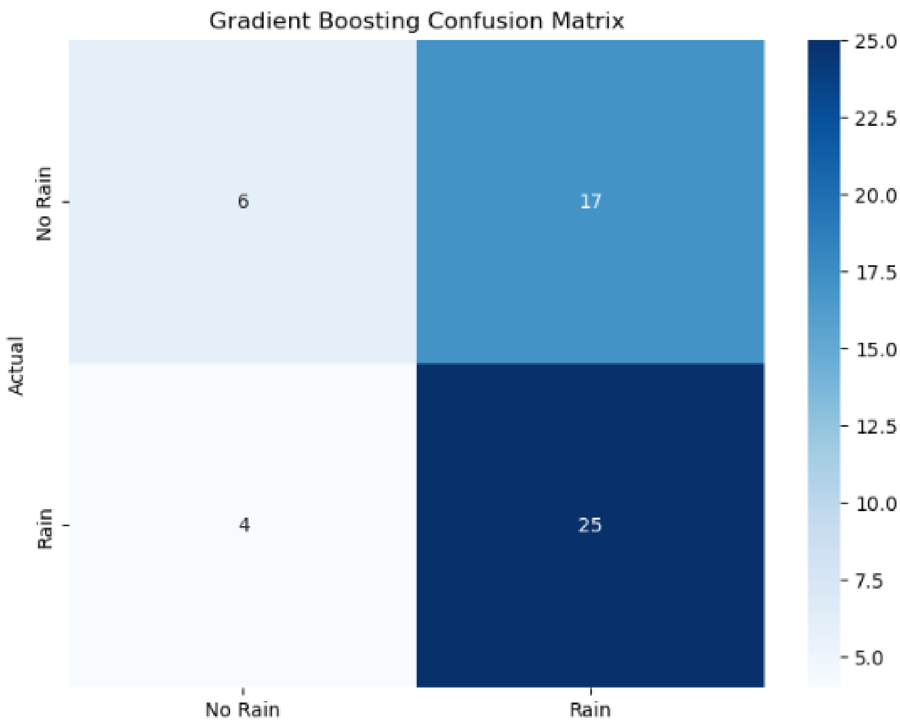
```
Training and evaluating KNN...
KNN Best Params: {'n_neighbors': 5}
KNN F1 Score: 0.7272727272727273
KNN Accuracy: 0.6538461538461539
KNN Classification Report:
              precision    recall  f1-score   support

           0       0.67      0.43      0.53        23
           1       0.65      0.83      0.73        29

    accuracy                           0.65        52
   macro avg       0.66      0.63      0.63        52
weighted avg       0.66      0.65      0.64        52
```



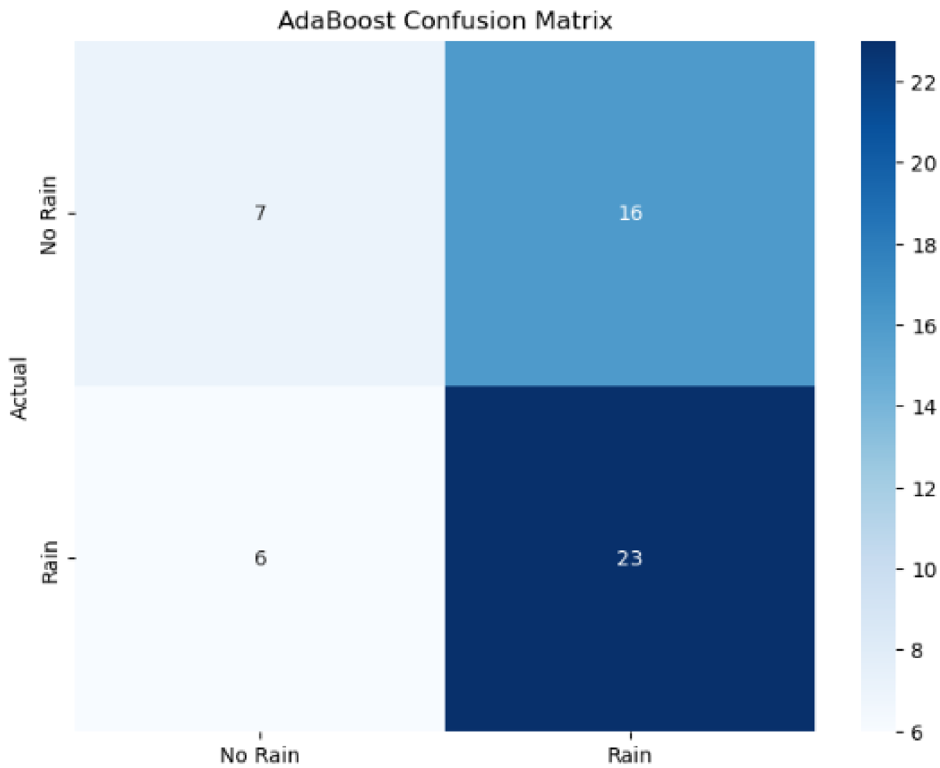
```
Training and evaluating Naive Bayes...
Naive Bayes Best Params: {}
Naive Bayes F1 Score: 0.7575757575757576
Naive Bayes Accuracy: 0.6923076923076923
Naive Bayes Classification Report:
              precision    recall  f1-score   support

           0       0.73      0.48      0.58        23
           1       0.68      0.86      0.76        29

    accuracy                           0.69        52
   macro avg       0.70      0.67      0.67        52
weighted avg       0.70      0.69      0.68        52
```



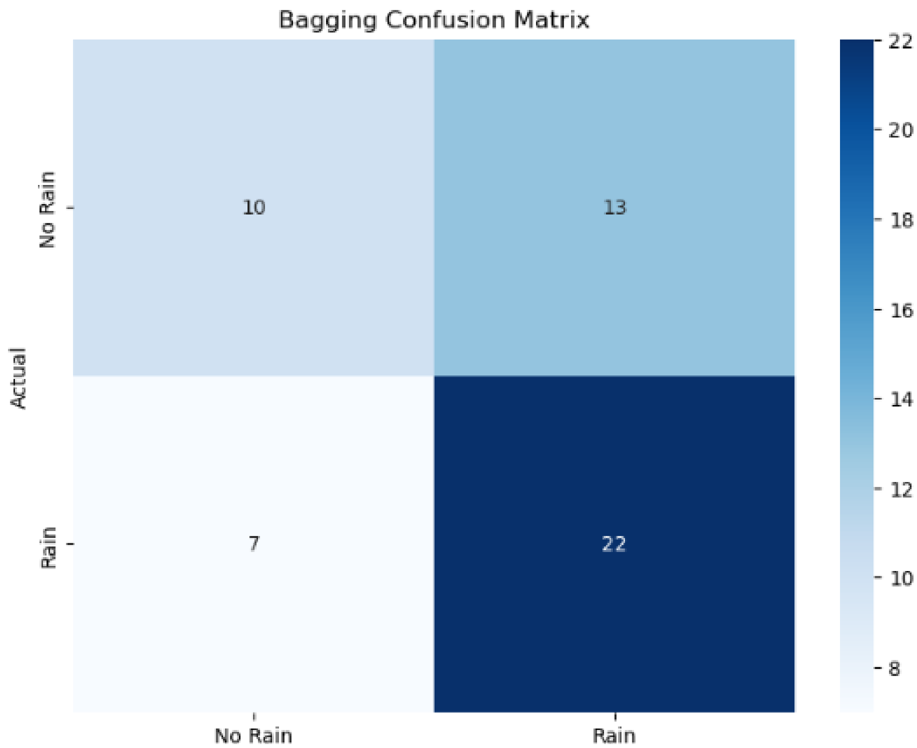
```
Training and evaluating Gradient Boosting...
Gradient Boosting Best Params: {'n_estimators': 200}
Gradient Boosting F1 Score: 0.704225352112676
Gradient Boosting Accuracy: 0.5961538461538461
Gradient Boosting Classification Report:
              precision    recall  f1-score   support

           0       0.60      0.26      0.36        23
           1       0.60      0.86      0.70        29

    accuracy                           0.60        52
   macro avg       0.60      0.56      0.53        52
weighted avg       0.60      0.60      0.55        52
```



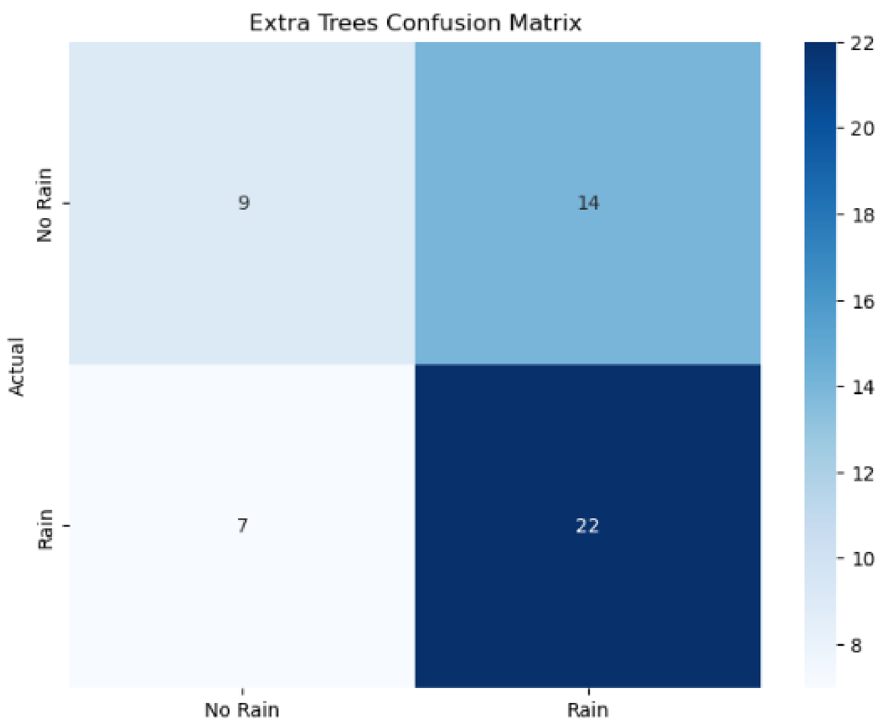
```
AdaBoost Best Params: {'n_estimators': 100}
AdaBoost F1 Score: 0.6764705882352942
AdaBoost Accuracy: 0.5769230769230769
AdaBoost Classification Report:
              precision    recall  f1-score   support

           0       0.54      0.30      0.39        23
           1       0.59      0.79      0.68        29

    accuracy                           0.58        52
   macro avg       0.56      0.55      0.53        52
weighted avg       0.57      0.58      0.55        52
```



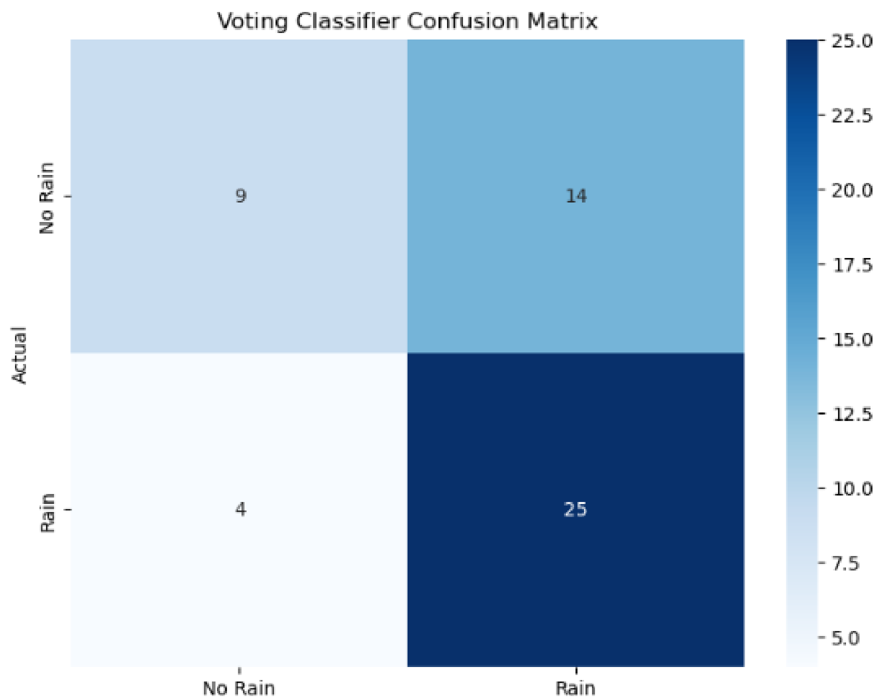
```
Training and evaluating Bagging...
Bagging Best Params: {'n_estimators': 100}
Bagging F1 Score: 0.6875
Bagging Accuracy: 0.6153846153846154
Bagging Classification Report:
              precision    recall  f1-score   support

           0       0.59      0.43      0.50        23
           1       0.63      0.76      0.69        29

    accuracy                           0.62        52
   macro avg       0.61      0.60      0.59        52
weighted avg       0.61      0.62      0.60        52
```



```
Training and evaluating Extra Trees...
Extra Trees Best Params: {'n_estimators': 200}
Extra Trees F1 Score: 0.676923076923077
Extra Trees Accuracy: 0.5961538461538461
Extra Trees Classification Report:
              precision    recall  f1-score   support

           0       0.56      0.39      0.46        23
           1       0.61      0.76      0.68        29

    accuracy                           0.60        52
   macro avg       0.59      0.57      0.57        52
weighted avg       0.59      0.60      0.58        52
```



```
Voting Classifier F1 Score: 0.7352941176470589
Voting Classifier Accuracy: 0.6538461538461539
Voting Classifier Classification Report:
              precision    recall  f1-score   support

           0       0.69      0.39      0.50        23
           1       0.64      0.86      0.74        29

    accuracy                           0.65        52
   macro avg       0.67      0.63      0.62        52
weighted avg       0.66      0.65      0.63        52
```



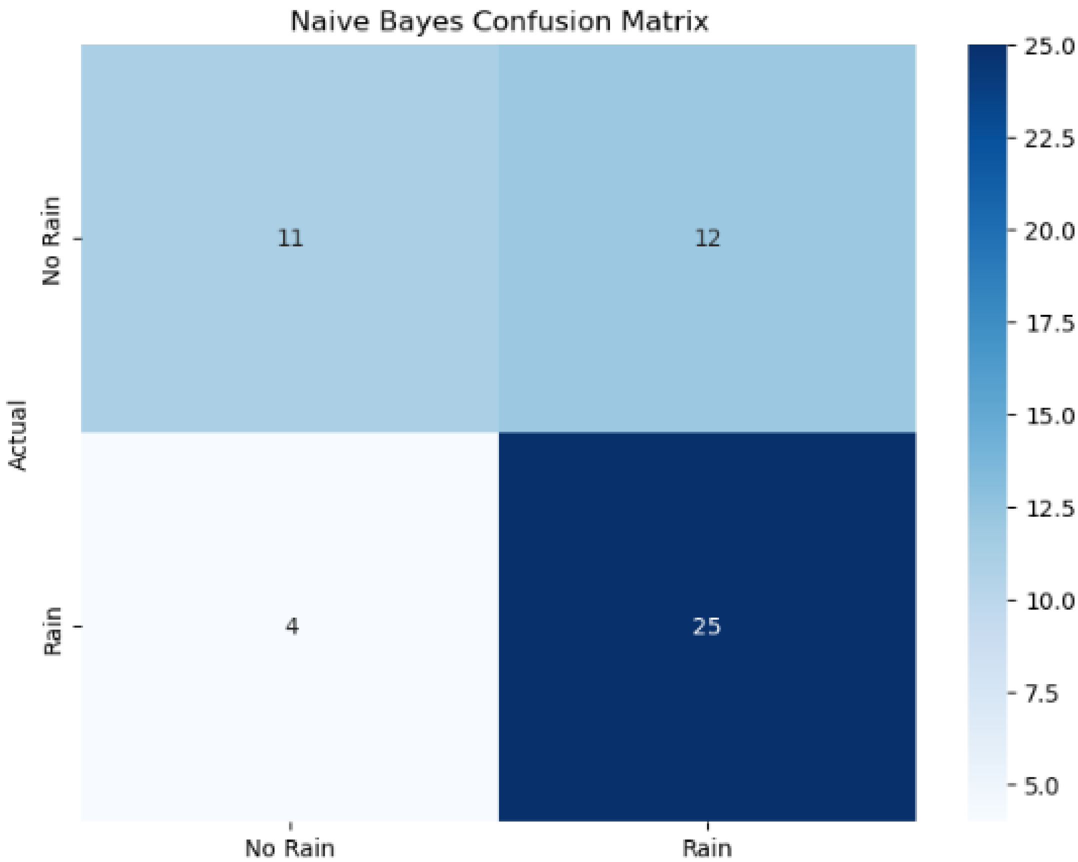
Model selection

[150]:
```python
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, f1_score
import seaborn as sns
import matplotlib.pyplot as plt

nb_model = GaussianNB()
nb_model.fit(X_train, y_train)

# Predict on the test set
y_pred_nb = nb_model.predict(X_test)
y_pred_proba_nb = nb_model.predict_proba(X_test)[:, 1]  # Probabilities for the positive class (Rain)

# Evaluate the model
print(f'Naive Bayes F1 Score: {f1_score(y_test, y_pred_nb)}')
print(f'Naive Bayes Classification Report: \n{classification_report(y_test, y_pred_nb)}')
print(f'Naive Bayes Accuracy: {accuracy_score(y_test, y_pred_nb)}')

# Plot confusion matrix
con_matrix_nb = confusion_matrix(y_test, y_pred_nb)
plt.figure(figsize=(8, 6))
sns.heatmap(con_matrix_nb, annot=True, fmt='d', cmap='Blues', xticklabels=['No Rain', 'Rain'], yticklabels=['No Rain', 'Rain'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Naive Bayes Confusion Matrix')
plt.show()

# Display predicted probabilities
print("Predicted probabilities for the test set:")
print(y_pred_proba_nb)
```

Naive Bayes F1 Score: 0.7575757575757576
Naive Bayes Classification Report:

	precision	recall	f1-score	support
0	0.73	0.48	0.58	23
1	0.68	0.86	0.76	29
accuracy			0.69	52
macro avg	0.70	0.67	0.67	52
weighted avg	0.70	0.69	0.68	52

Naive Bayes Accuracy: 0.6923076923076923



```
Predicted probabilities for the test set:
[0.99602422 0.83318923 0.13003297 0.93342485 0.98174218 0.84337889
 0.51741545 0.24710529 0.77596029 0.87632233 0.16679479 0.97647446
 0.97523924 0.99771879 0.83900549 0.99647236 0.15857431 0.39837369
 0.99081998 0.25317155 0.96498878 0.99359259 0.99216988 0.99323032
 0.61363981 0.99127105 0.86154772 0.2714948  0.41205313 0.97740015
 0.95055616 0.77186365 0.21252871 0.96116906 0.94219651 0.23901582
 0.65234905 0.98364051 0.17731031 0.93641683 0.14951767 0.99618046
 0.96008472 0.52084565 0.11864727 0.97689385 0.86857605 0.99258572
 0.9339639  0.12431659 0.23202685 0.98472987]
```

Part: System Design for Real-Time Rain Prediction

1. System Overview

As an MLOps Engineer, our goal is to design a system that continuously ingests real-time weather data from IoT sensors, processes the data to handle potential sensor malfunctions, and predicts the probability of rain for the next 21 days. The system must ensure high availability, data accuracy, and fault tolerance.

2. System Diagram

Below is the system diagram illustrating the data flow from IoT sensors to the end-user.

(Insert system diagram here)

3. Component Descriptions

3.1 IoT Sensors & Data Collection

- Sensors deployed in agricultural fields collect weather parameters (temperature, humidity, wind speed, rainfall).
- Data is transmitted to an edge device every minute.

3.2 Edge Processing & Data Validation

- A lightweight processing unit (e.g., Raspberry Pi) filters out erroneous sensor readings.
- Statistical techniques (e.g., Z-score, IQR) help detect outliers.
- Missing values are handled using interpolation techniques.

3.3 Cloud Data Pipeline (Storage & Processing)

- Cleaned data is sent to a cloud storage service (e.g., AWS S3, Google Cloud Storage).
- A streaming service (e.g., Apache Kafka, AWS Kinesis) manages real-time data ingestion.
- A processing framework (e.g., Apache Spark, AWS Lambda) prepares data for the ML model.

3.4 Machine Learning Model

- A trained model (Random Forest/Gradient Boosting) predicts the probability of rain.
- The model runs daily predictions using the most recent data.
- Model retraining occurs periodically to improve accuracy.

3.5 API & Dashboard

- Predictions are served through a REST API.
- A web dashboard displays forecasted rain probability for farmers.
- Alerts are sent via SMS or app notifications if high rain probability is detected.

4. Error Handling & Fault Tolerance

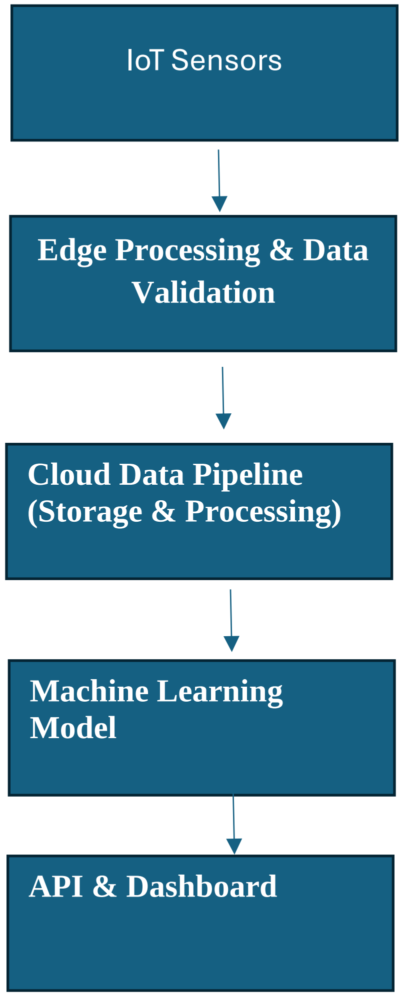
- **Sensor Malfunctions:** If data anomalies exceed a threshold, the system excludes faulty sensors.
- **Network Failures:** Edge processing enables local data storage until connectivity is restored.
- **Model Degradation:** Automated monitoring detects accuracy drop, triggering model retraining.

5. Conclusion

This system ensures real-time, reliable rain predictions for farmers. By integrating IoT devices, edge processing, cloud-based storage, and ML predictions, it enhances decision-making in smart agriculture.

6. System Diagram

The diagram below illustrates the data flow from IoT sensors to the end-user:


IoT Sensors
Edge Processing & Data Validation
Cloud Data Pipeline (Storage & Processing)
Machine Learning Model
API & Dashboard