In this project, I developed a weather prediction model using the K-Nearest Neighbors (KNN) algorithm. The dataset consists of weather conditions over several years, including temperature, humidity, wind speed, and other relevant features. The project involved the following steps:

1. **Data Preprocessing**: Handled missing values, normalized the data, and performed feature engineering to enhance the dataset's predictive power.
2. **Exploratory Data Analysis (EDA)**: Analyzed the distribution of weather conditions and visualized the relationships between different features using scatter plots and heatmaps.
3. **Model Development**: Implemented the KNN algorithm, optimizing the number of neighbors (k) using cross-validation to achieve the best performance.
4. **Model Evaluation:** Evaluated the model using accuracy, precision, recall, and F1-score. The final model achieved an impressive accuracy of 93.39%.
5. **Results**: Presented confusion matrices and classification reports to provide a detailed evaluation of the model's performance.

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import time

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_sc
ore, f1_score


import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
/kaggle/input/weather-prediction/seattle-weather.csv
```

Data Preprocessing

In [2]:

```
df = pd.read_csv('/kaggle/input/weather-prediction/seattle-weather.csv')
df.head()
```

Out[2]:

	date	precipitation	temp_max	temp_min	wind	weather
0	2012-01-01	0.0	12.8	5.0	4.7	drizzle
1	2012-01-02	10.9	10.6	2.8	4.5	rain
2	2012-01-03	0.8	11.7	7.2	2.3	rain
3	2012-01-04	20.3	12.2	5.6	4.7	rain
4	2012-01-05	1.3	8.9	2.8	6.1	rain

In [3]:

```
df.drop(columns=['date'], inplace=True)
```

In [4]:

```
df.isnull().sum()
```

Out[4]:

```
precipitation    0
temp_max         0
temp_min         0
wind             0
weather          0
dtype: int64
```

In [5]:

```
df[df.duplicated()]
```

Out[5]:

	precipitation	temp_max	temp_min	wind	weather
188	0.0	26.7	12.8	3.8	sun
629	0.0	21.1	13.3	2.5	sun
748	0.0	9.4	0.6	2.2	sun
751	0.0	10.0	1.7	1.5	sun
863	0.0	26.7	12.8	3.8	sun
959	0.0	27.8	15.0	2.8	sun
1019	0.0	20.6	11.1	3.3	sun
1346	0.0	22.8	13.3	2.4	sun

In [6]:

```
df.head(10)
```

Out[6]:

	precipitation	temp_max	temp_min	wind	weather
0	0.0	12.8	5.0	4.7	drizzle
1	10.9	10.6	2.8	4.5	rain
2	0.8	11.7	7.2	2.3	rain
3	20.3	12.2	5.6	4.7	rain
4	1.3	8.9	2.8	6.1	rain
5	2.5	4.4	2.2	2.2	rain
6	0.0	7.2	2.8	2.3	rain
7	0.0	10.0	2.8	2.0	sun
8	4.3	9.4	5.0	3.4	rain
9	1.0	6.1	0.6	3.4	rain

In [7]:

```
# Define a mapping dictionary
mapping = {'drizzle': 0, 'fog': 1, 'rain': 2, 'snow': 3, 'sun': 4}

# Apply the mapping to the 'Category' column
df['weather'] = df['weather'].map(mapping)
print(df)
```

```
      precipitation  temp_max  temp_min  wind  weather
0               0.0      12.8       5.0   4.7        0
1              10.9      10.6       2.8   4.5        2
2               0.8      11.7       7.2   2.3        2
3              20.3      12.2       5.6   4.7        2
4               1.3       8.9       2.8   6.1        2
...             ...       ...       ...   ...      ...
1456            8.6       4.4       1.7   2.9        2
1457            1.5       5.0       1.7   1.3        2
1458            0.0       7.2       0.6   2.6        1
1459            0.0       5.6      -1.0   3.4        4
1460            0.0       5.6      -2.1   3.5        4

[1461 rows x 5 columns]
```

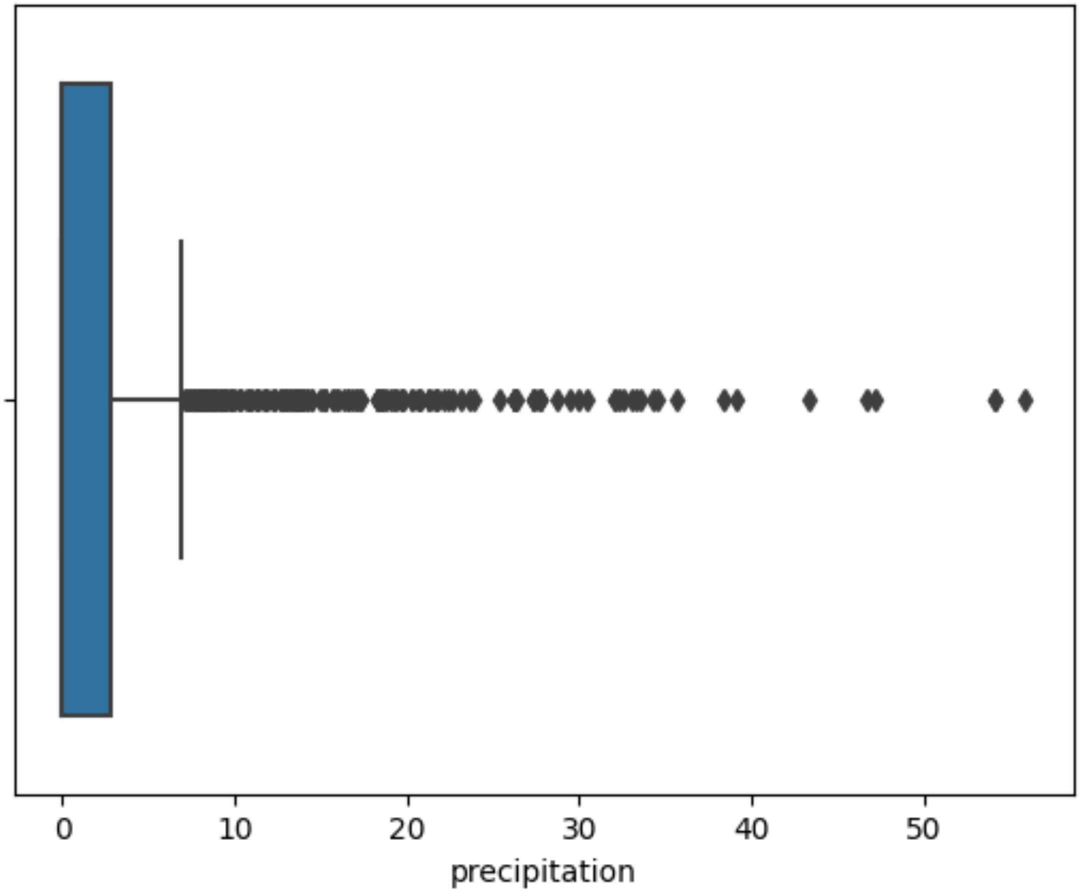
Cleaning Outliers

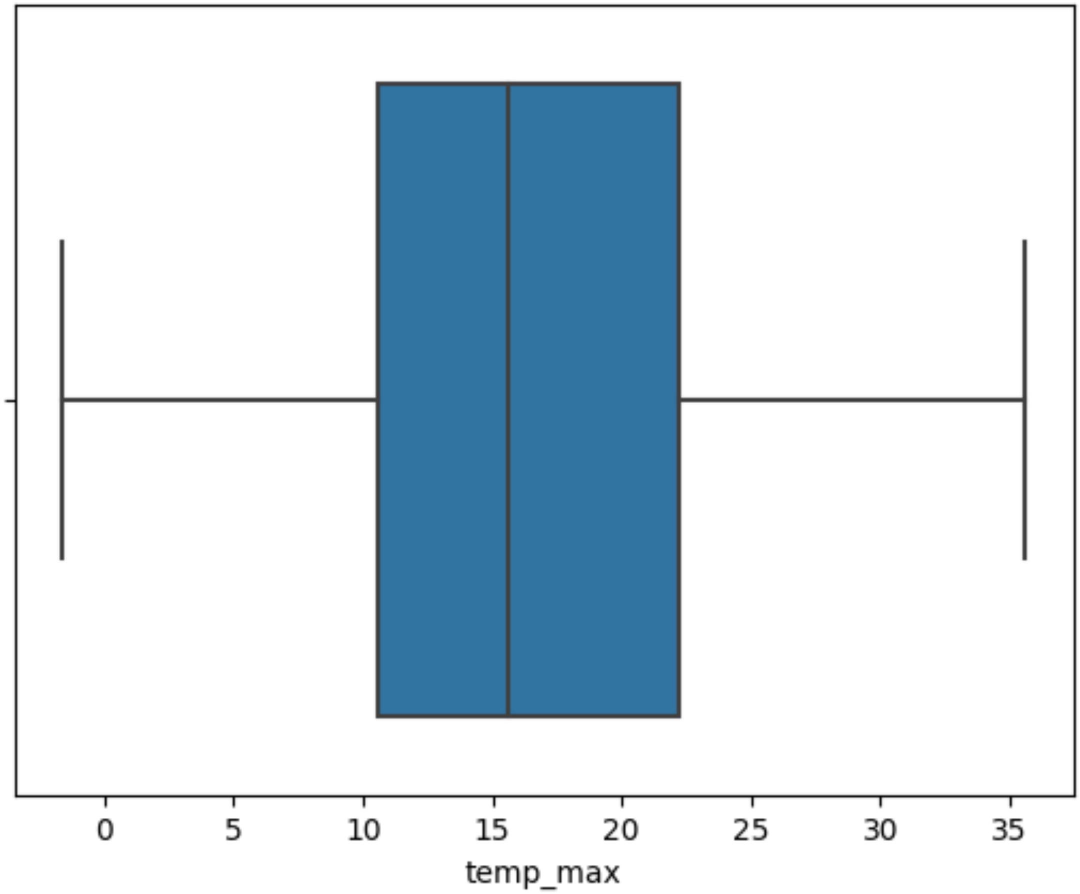
In [8]:
```
column = ['precipitation','temp_max','temp_min', 'wind']
df[column].describe()
```

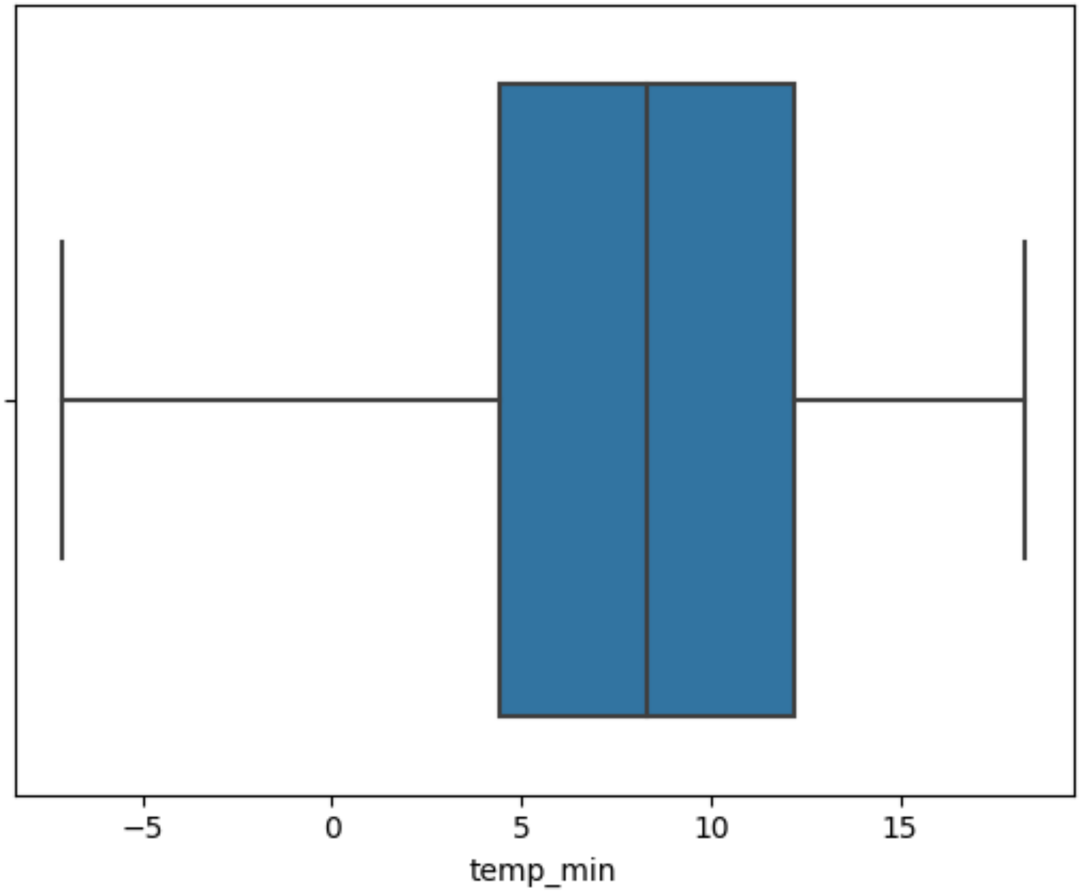
Out[8]:

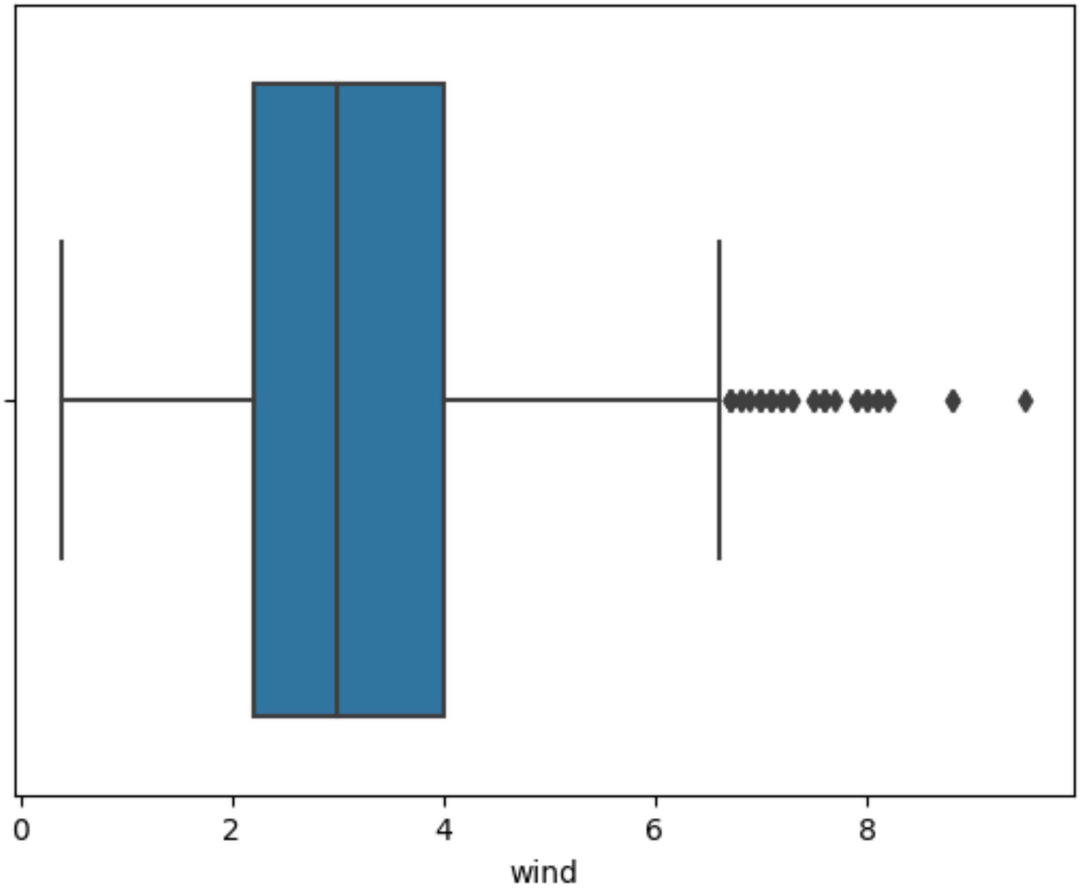
	precipitation	temp_max	temp_min	wind
count	1461.000000	1461.000000	1461.000000	1461.000000
mean	3.029432	16.439083	8.234771	3.241136
std	6.680194	7.349758	5.023004	1.437825
min	0.000000	-1.600000	-7.100000	0.400000
25%	0.000000	10.600000	4.400000	2.200000
50%	0.000000	15.600000	8.300000	3.000000
75%	2.800000	22.200000	12.200000	4.000000
max	55.900000	35.600000	18.300000	9.500000

In [9]:
```
for cols in column:
  sns.boxplot(x=df[cols])
  plt.show()
```




0
5
10
15
20
25
30
35
temp_max


−5
0
5
10
15
temp_min

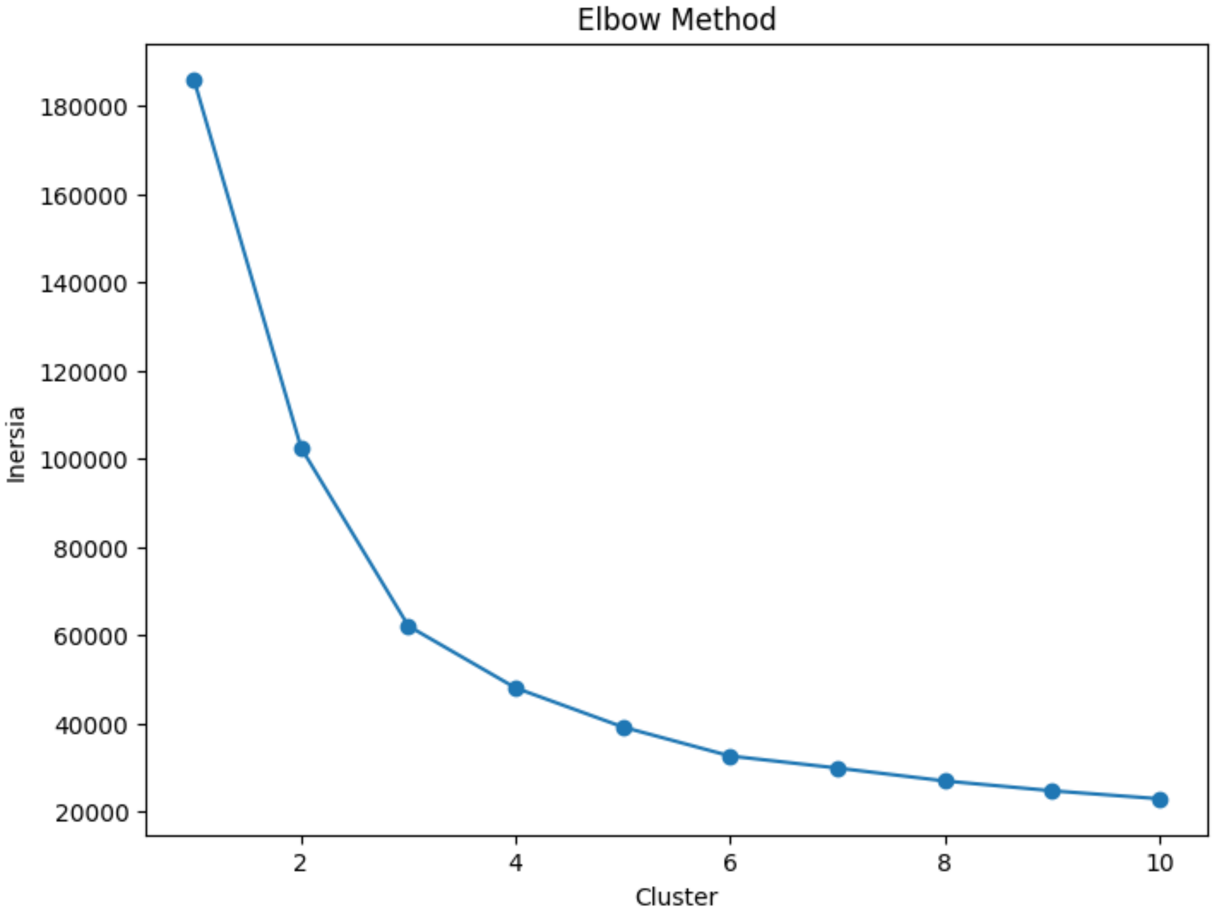


K-Means Clustering (Elbow Method)

In [10]:

```
inertias = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, random_state=42,  n_init=10)
    kmeans.fit(df)
    inertias.append(kmeans.inertia_)

plt.figure(figsize=(8, 6))
plt.plot(range(1, 11), inertias, marker='o')
plt.xlabel('Cluster')
plt.ylabel('Inersia')
plt.title('Elbow Method')
plt.show()
```



In [11]:

```
scaler = StandardScaler()
scaled_features = scaler.fit_transform(df)

n_clusters = 5

kmeans = KMeans(n_clusters=n_clusters, random_state=42,  n_init=10)
df['cluster'] = kmeans.fit_predict(scaled_features)

df.to_csv('data_baru.csv', index=False)
```

In [12]:

```
df_clean = pd.read_csv("data_baru.csv")
df_clean.head(100)
```

Out[12]:

	precipitation	temp_max	temp_min	wind	weather	cluster
0	0.0	12.8	5.0	4.7	0	1
1	10.9	10.6	2.8	4.5	2	1
2	0.8	11.7	7.2	2.3	2	4
3	20.3	12.2	5.6	4.7	2	2
4	1.3	8.9	2.8	6.1	2	1
...	...	...	...	...	...	...
95	4.6	9.4	2.8	1.8	3	4
96	0.3	11.1	3.3	2.6	2	4
97	0.0	16.1	1.7	4.3	4	1
98	0.0	21.1	7.2	4.1	4	3
99	0.0	20.0	6.1	2.1	4	3

100 rows × 6 columns

Split Dataset

In [13]:

```
X = df.drop(['cluster'], axis=1)
y = df['cluster']
```

In [14]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.3, random_state = 42)
```

Model Development

In [15]:

```
start_time = time.time()
```

In [16]:

```
knn = KNeighborsClassifier()

param_grid = {'n_neighbors': [3, 5, 7, 9], 'weights': ['uniform', 'distance'], 'metric': ['euclidean', 'manhattan']}
grid_search = GridSearchCV(knn, param_grid, cv=4)
grid_search.fit(X_train, y_train)

print("Best Parameter", grid_search.best_params_)

best_knn = grid_search.best_estimator_

best_knn.fit(X_train, y_train)
y_pred = best_knn.predict(X_test)
```

```
Best Parameter {'metric': 'manhattan', 'n_neighbors': 9, 'weights': 'distance'}
```

Results

In [17]:

```
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

precision = precision_score(y_test, y_pred, average='weighted')
print("Precicion:", precision)

recall = recall_score(y_test, y_pred, average='weighted')
print("Recall:", recall)

f1 = f1_score(y_test, y_pred, average='weighted')
print("F1 Score:", f1)
```

```
Accuracy: 0.9339407744874715
Precicion: 0.9336140824406746
Recall: 0.9339407744874715
F1 Score: 0.9318768225059251
```

In [18]:

```
end_time = time.time()

process_time = end_time - start_time

print(f"Time run: {process_time} second")
```

```
Time run: 1.1721363067626953 second
```

Conclusion: The KNN-based weather prediction model achieved high accuracy, demonstrating the algorithm's effectiveness for this task. Future work includes exploring more advanced models like Random Forest and Gradient Boosting to further improve prediction accuracy.