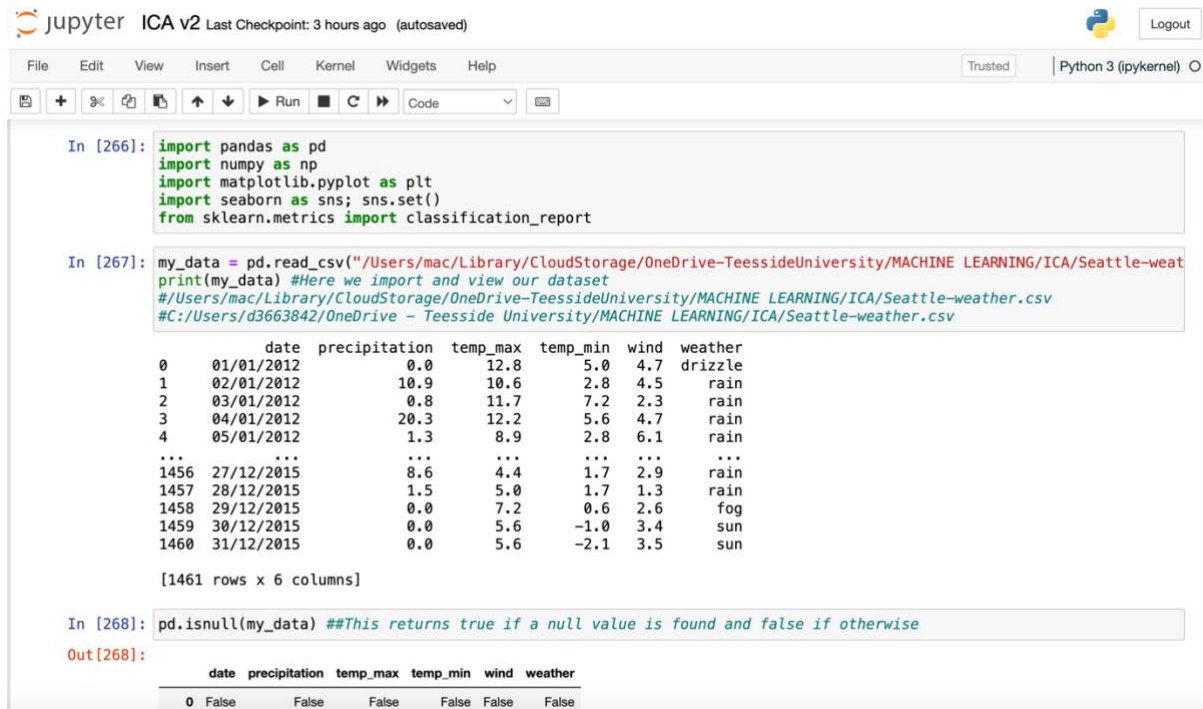


Weather Prediction using Machine Learning Classification Models by exploring the influencing factors using Python.

Here, we imported the data set and previewed the data.



The screenshot shows a Jupyter Notebook interface with the following content:

```
In [266]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
from sklearn.metrics import classification_report
```

```
In [267]: my_data = pd.read_csv("/Users/mac/Library/CloudStorage/OneDrive-TeessideUniversity/MACHINE LEARNING/ICA/Seattle-weat
print(my_data) #Here we import and view our dataset
#C:/Users/d3663842/OneDrive - Teesside University/MACHINE LEARNING/ICA/Seattle-weather.csv
```

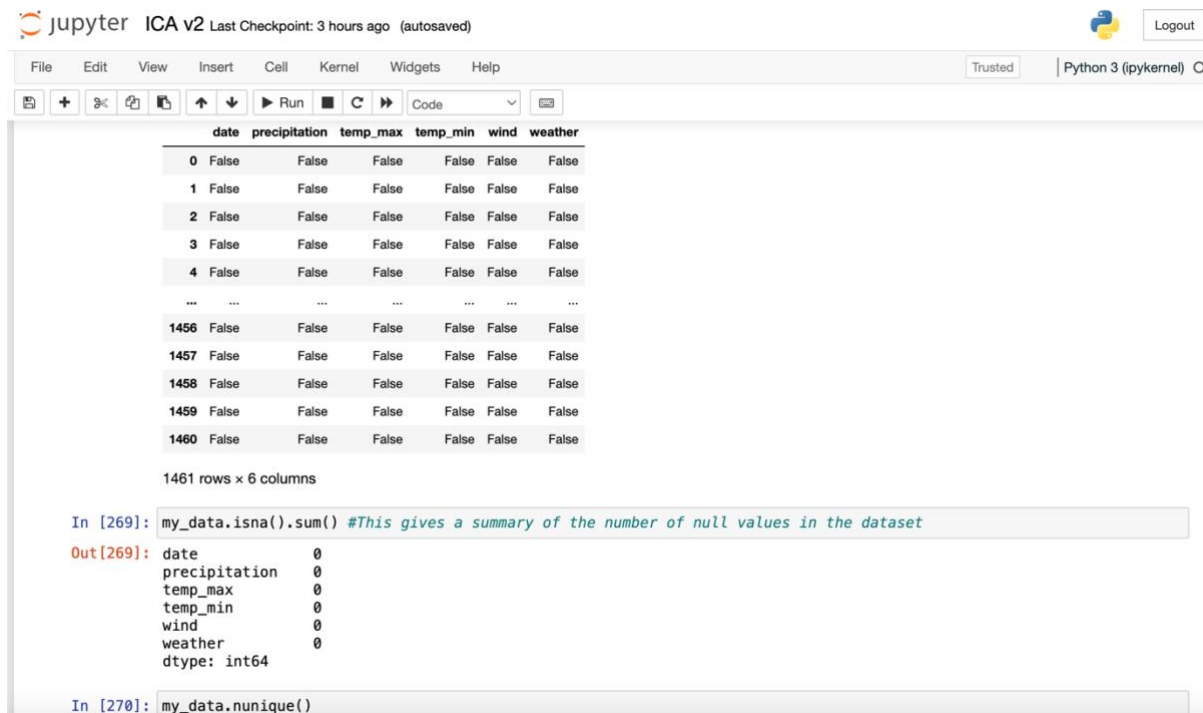
	date	precipitation	temp_max	temp_min	wind	weather
0	01/01/2012	0.0	12.8	5.0	4.7	drizzle
1	02/01/2012	10.9	10.6	2.8	4.5	rain
2	03/01/2012	0.8	11.7	7.2	2.3	rain
3	04/01/2012	20.3	12.2	5.6	4.7	rain
4	05/01/2012	1.3	8.9	2.8	6.1	rain
...
1456	27/12/2015	8.6	4.4	1.7	2.9	rain
1457	28/12/2015	1.5	5.0	1.7	1.3	rain
1458	29/12/2015	0.0	7.2	0.6	2.6	fog
1459	30/12/2015	0.0	5.6	-1.0	3.4	sun
1460	31/12/2015	0.0	5.6	-2.1	3.5	sun

[1461 rows x 6 columns]

```
In [268]: pd.isnull(my_data) ##This returns true if a null value is found and false if otherwise
```

	date	precipitation	temp_max	temp_min	wind	weather
0	False	False	False	False	False	False

Here we begin running some checks on the data like checking if there are null values.



The screenshot shows a Jupyter Notebook interface with the following content:

	date	precipitation	temp_max	temp_min	wind	weather
0	False	False	False	False	False	False
1	False	False	False	False	False	False
2	False	False	False	False	False	False
3	False	False	False	False	False	False
4	False	False	False	False	False	False
...
1456	False	False	False	False	False	False
1457	False	False	False	False	False	False
1458	False	False	False	False	False	False
1459	False	False	False	False	False	False
1460	False	False	False	False	False	False

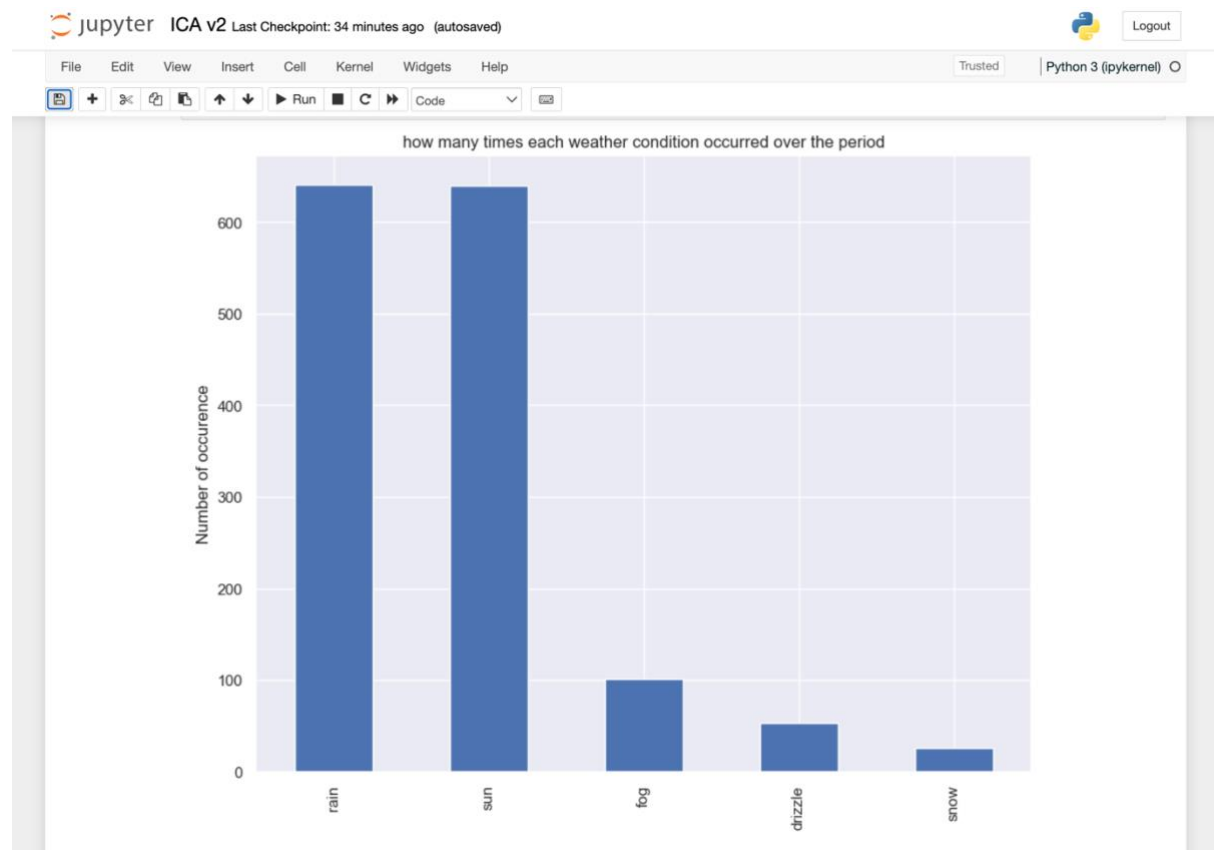
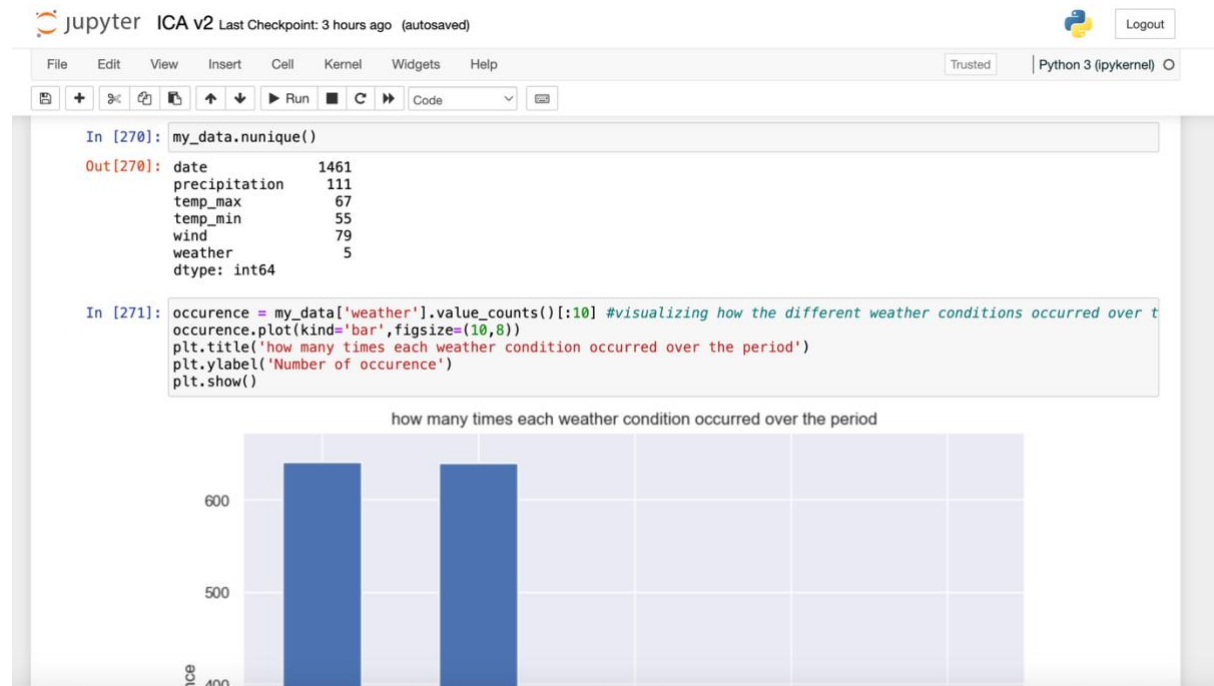
1461 rows x 6 columns

```
In [269]: my_data.isna().sum() #This gives a summary of the number of null values in the dataset
```

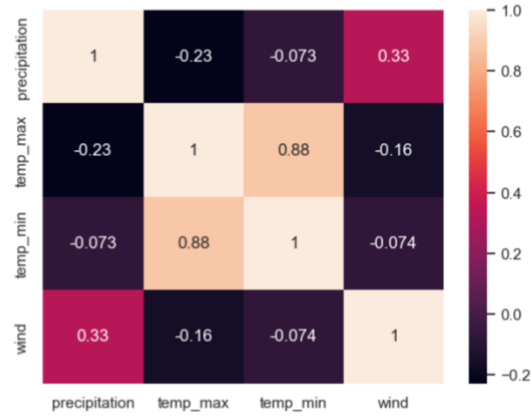
```
Out[269]: date          0
precipitation  0
temp_max      0
temp_min      0
wind          0
weather       0
dtype: int64
```

```
In [270]: my_data.nunique()
```

Here we begin doing some plots to visualize our data and some exploratory data analysis

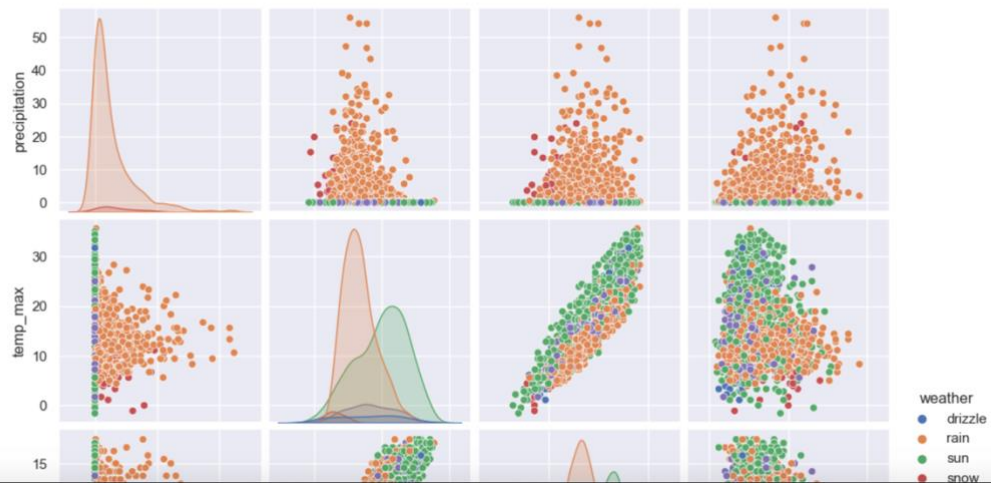


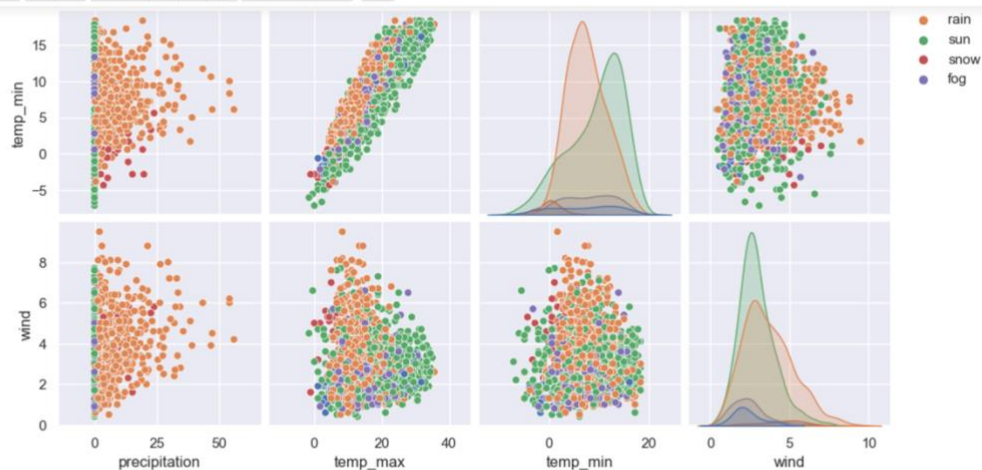
```
In [272]: heatmap = my_data.corr() # Compute correlation matrix
sns.heatmap(heatmap, annot=True) # Plot heatmap with annotations
plt.show() # Show the plot
```



```
In [273]: plt.figure(figsize=(13,17)) #pairplot to compare the correlation and relationship between features
sns.pairplot(data = my_data, hue='weather')
plt.show()
```

<Figure size 1300x1700 with 0 Axes>

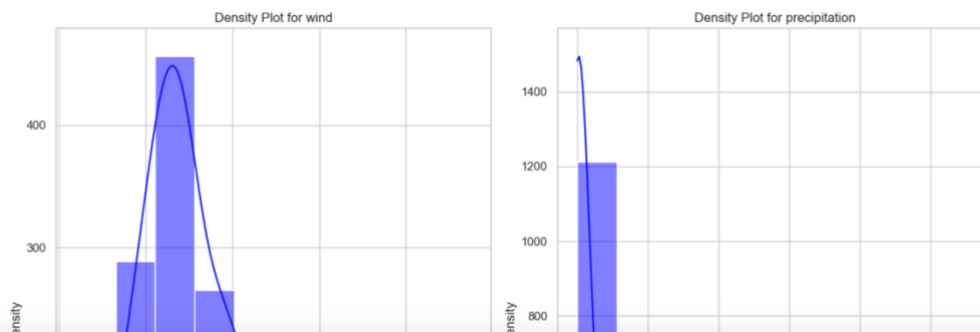


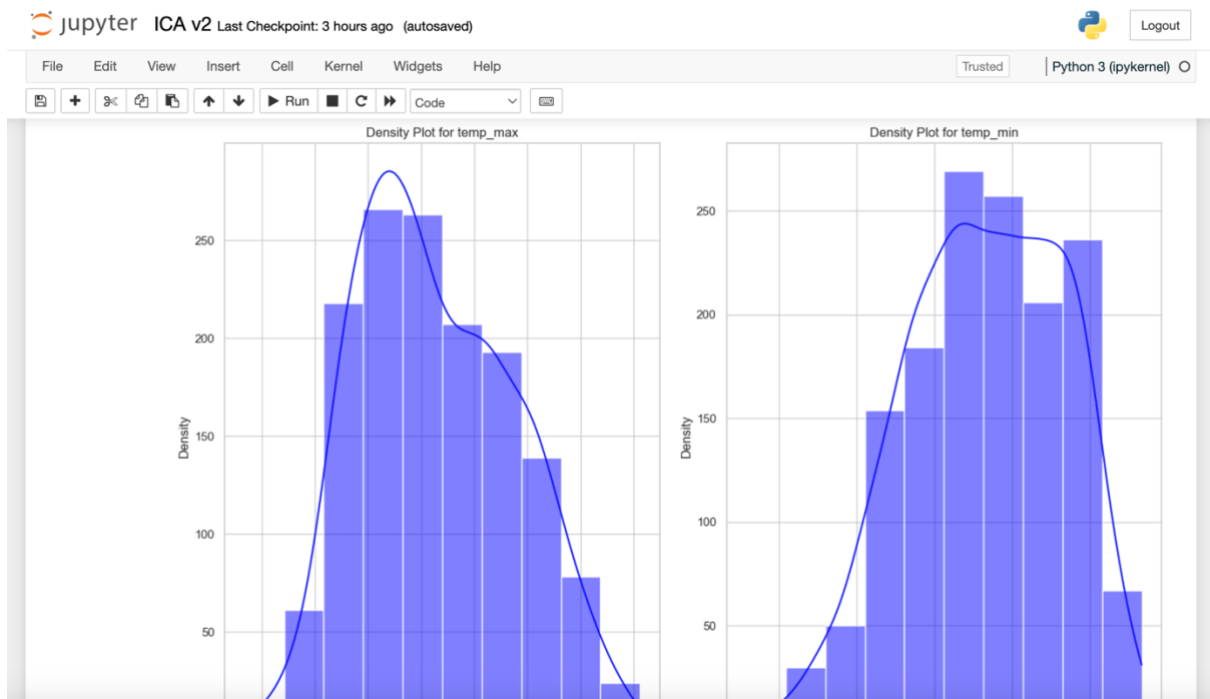
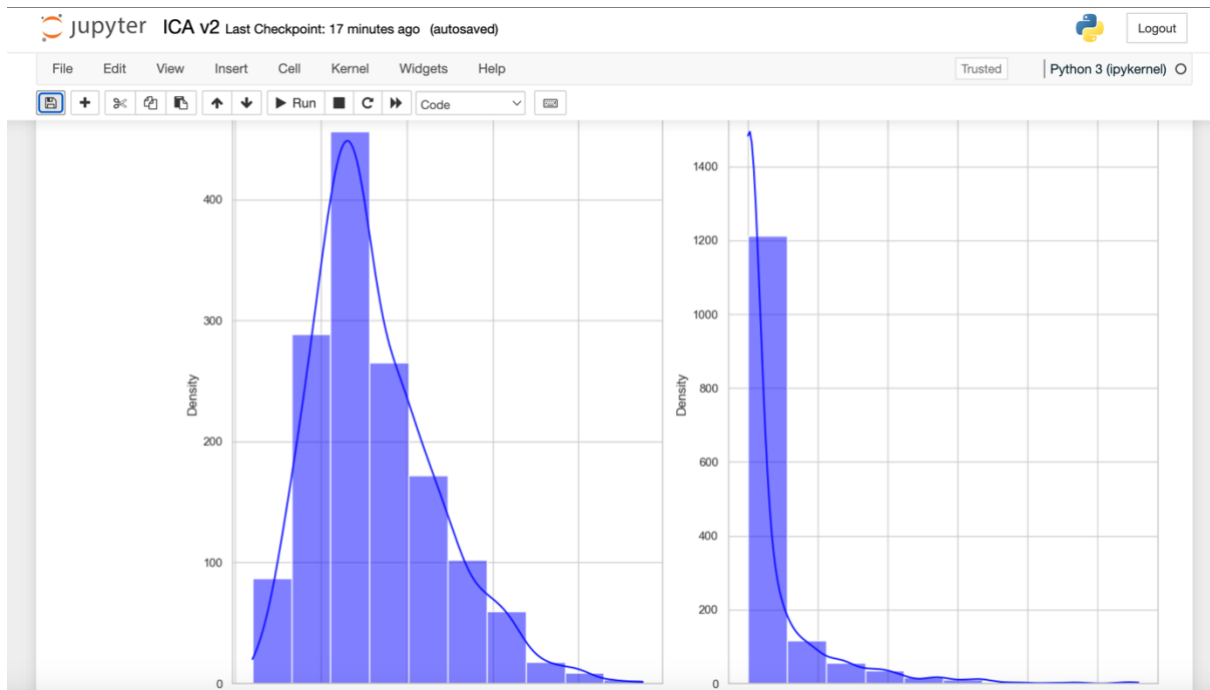


```
In [274]: data = my_data
numeric = ['wind', 'precipitation', 'temp_max', 'temp_min']
sns.set(style="whitegrid")
plt.figure(figsize=(13,17))
for i, var in enumerate(numeric, 1):
```

```
In [274]: data = my_data
numeric = ['wind', 'precipitation', 'temp_max', 'temp_min']
sns.set(style="whitegrid")
plt.figure(figsize=(13,17))
for i, var in enumerate(numeric, 1):
    plt.subplot(2, 2, i)
    sns.histplot(data[var], kde=True, color='blue', bins=10)
    plt.title(f'Density Plot for {var}')
    plt.xlabel(var)
    plt.ylabel('Density')

plt.tight_layout()
plt.show()
```





Here we scale and normalize the data:

```
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File Edit View Insert Cell Kernel Widgets Help Trusted Python 3 (ipykernel)
In [275]: from sklearn.preprocessing import MinMaxScaler
def dataset_minmax(my_data): #finding the minimum and maximum values for each column
    minmax = list()
    for i in range(len(my_data[0])):
        col_values = [row[i] for row in my_data]
        value_min = min(col_values)
        value_max = max(col_values)
        minmax.append([value_min, value_max])
    return minmax

In [276]: from sklearn.preprocessing import MinMaxScaler #Normalizing the data
scaler = MinMaxScaler()
data_scaled = (scaler.fit_transform(my_data[numeric]))
print(data_scaled)

[[0.47252747 0.          0.38709677 0.47637795]
 [0.45054945 0.19499106 0.32795699 0.38976378]
 [0.20879121 0.01431127 0.35752688 0.56299213]
 ...
 [0.24175824 0.          0.23655914 0.30314961]
 [0.32967033 0.          0.19354839 0.24015748]
 [0.34065934 0.          0.19354839 0.19685039]]

In [277]: def cross_validation_split(my_data, n_folds): #split the data into n-folds
my_data_split = list()
my_data_copy = list(my_data)
fold_size = int(len(my_data) / n_folds)
for _ in range(n_folds):
    fold = list()
    while len(fold) < fold_size:
        index = randrange(len(my_data_copy))
        fold.append(my_data_copy[index])
    my_data_split.append(fold)
    my_data_copy = [my_data_copy[i] for i in range(len(my_data_copy)) if i not in index]
```

Here we split the data for training and testing and begin applying the models

```
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File Edit View Insert Cell Kernel Widgets Help Trusted Python 3 (ipykernel)
In [278]: def accuracy_metric(actual, predicted):
correct = 0
for i in range(len(actual)):
    if actual[i] == predicted[i]:
        correct += 1
return correct / float(len(actual)) * 100.0

In [279]: from sklearn.model_selection import train_test_split #Split the dataset for training and testing using a 60-30 ratio
Y = my_data['weather']
X = my_data.drop(columns=['weather', 'date'])
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3, random_state=42)

print('X train shape: ', X_train.shape)
print('Y train shape: ', Y_train.shape)
print('X test shape: ', X_test.shape)
print('Y test shape: ', Y_test.shape)

X train shape: (1022, 4)
Y train shape: (1022,)
X test shape: (439, 4)
Y test shape: (439,)

K-Nearest Neighbour

In [280]: from sklearn.neighbors import KNeighborsClassifier
neighbors = np.arange(1, 9) #plotting to find the n_neighbors
train_accuracy = np.empty(len(neighbors))
for i, k in enumerate(neighbors):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, Y_train)
```

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Python 3 (ipykernel)



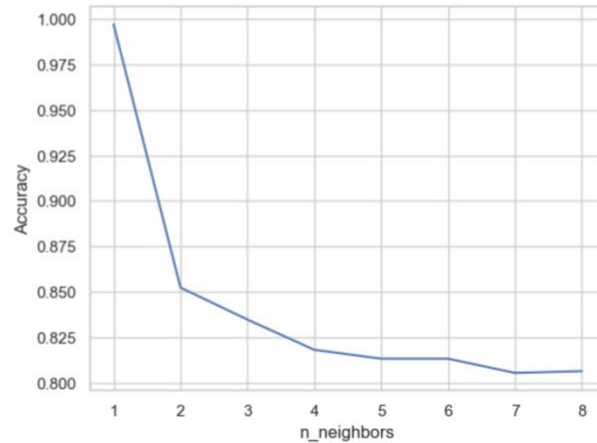









```
plt.xlabel('n_neighbors')
plt.ylabel('Accuracy')
plt.show()
```



In [281]: `!pip install scikit-learn`

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Trusted

Python 3 (ipykernel)












```
In [283]: from sklearn.model_selection import GridSearchCV #using Grid search for hyper-parameter tuning
weight_options = ['uniform', 'distance']
metric_options = ['euclidean', 'minkowski']
number = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
# create a parameter grid to map the parameter names to the values that should be searched using Grid search
param_grid = dict(n_neighbors=number, weights=weight_options, metric=metric_options)
#param_grid = dict(n_neighbors=number)
print(param_grid)
grid = GridSearchCV(knn, param_grid, cv=10, scoring='accuracy', return_train_score=False)
grid.fit(X_train, Y_train)
print(grid.best_score_)
print(grid.best_params_)
pd.DataFrame(grid.cv_results_)[['mean_test_score', 'std_test_score', 'params']]

{'n_neighbors': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10], 'weights': ['uniform', 'distance'], 'metric': ['euclidean', 'minkowski']}
0.7563011612411955
{'metric': 'euclidean', 'n_neighbors': 7, 'weights': 'distance'}
```

Out[283]:

	mean_test_score	std_test_score	params
0	0.711289	0.039655	{'metric': 'euclidean', 'n_neighbors': 1, 'wei...
1	0.711289	0.039655	{'metric': 'euclidean', 'n_neighbors': 1, 'wei...
2	0.666324	0.034778	{'metric': 'euclidean', 'n_neighbors': 2, 'wei...
3	0.711289	0.039655	{'metric': 'euclidean', 'n_neighbors': 2, 'wei...
4	0.721083	0.038843	{'metric': 'euclidean', 'n_neighbors': 3, 'wei...
5	0.725976	0.032004	{'metric': 'euclidean', 'n_neighbors': 3, 'wei...
6	0.728898	0.028955	{'metric': 'euclidean', 'n_neighbors': 4, 'wei...
7	0.736741	0.034421	{'metric': 'euclidean', 'n_neighbors': 4, 'wei...


```
In [284]: knn_model = KNeighborsClassifier(metric = 'euclidean', n_neighbors = 7, weights = 'distance')
knn_model.fit(X_train, Y_train) #Applying KNN algorithm to the data
```

```
Out[284]: KNeighborsClassifier
KNeighborsClassifier(metric='euclidean', n_neighbors=7, weights='distance')
```

```
In [285]: y_pred = knn_model.predict(X_test)
```

```
In [286]: from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
accuracy_score(Y_test, y_pred) #printing the accuracy score
```

```
Out[286]: 0.7608200455580866
```

```
In [287]: confusion_matrix(Y_test, y_pred) #printing confusion matrix to check for data balance and distribution
```

```
Out[287]: array([[ 1,  1,  0,  0, 12],
 [ 1,  1,  2,  0, 28],
 [ 1,  0, 164,  0, 27],
 [ 0,  1,  4,  0,  3],
 [ 3,  9, 13,  0, 168]])
```

```
In [288]: print(Y_train.value_counts())
```

```
rain      449
sun       447
fog        69
drizzle    39
snow       18
Name: weather, dtype: int64
```

Balancing the dataset using SMOTETOMEK

```
In [291]: from imblearn.combine import SMOTETomek #importing smote tomek library
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
```

```
In [292]: # Applying Smote Tomek to balance the data
smote_tomek = SMOTETomek()
X_resampled, Y_resampled = smote_tomek.fit_resample(X_train, Y_train)
```

```
In [293]: # Split the resampled data into train and test sets
X_train_resampled, X_test_resampled, Y_train_resampled, Y_test_resampled = train_test_split(X_resampled, Y_resampled)
```

```
In [294]: # performing grid search on the resampled data
weight_options = ['uniform', 'distance']
metric_options = ['euclidean', 'minkowski']
number = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
# create a parameter grid: map the parameter names to the values that should be searched
param_grid = dict(n_neighbors=number, weights=weight_options, metric=metric_options)
#param_grid = dict(n_neighbors=number)
print(param_grid)
grid = GridSearchCV(knn, param_grid, cv=10, scoring='accuracy', return_train_score=False)
grid.fit(X_train_resampled, Y_train_resampled)
print(grid.best_score_)
print(grid.best_params_)
pd.DataFrame(grid.cv_results_)[['mean_test_score', 'std_test_score', 'params']]

{'n_neighbors': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10], 'weights': ['uniform', 'distance'], 'metric': ['euclidean', 'minkowski']}
0.8520547945205479
{'metric': 'euclidean', 'n_neighbors': 1, 'weights': 'uniform'}
```


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	mean_test_score	std_test_score	params
0	0.852055	0.024734	{'metric': 'euclidean', 'n_neighbors': 1, 'wei...
1	0.852055	0.024734	{'metric': 'euclidean', 'n_neighbors': 1, 'wei...
2	0.805479	0.023368	{'metric': 'euclidean', 'n_neighbors': 2, 'wei...
3	0.852055	0.024734	{'metric': 'euclidean', 'n_neighbors': 2, 'wei...
4	0.806849	0.025774	{'metric': 'euclidean', 'n_neighbors': 3, 'wei...
5	0.831507	0.024543	{'metric': 'euclidean', 'n_neighbors': 3, 'wei...
6	0.791096	0.025490	{'metric': 'euclidean', 'n_neighbors': 4, 'wei...
7	0.838356	0.023766	{'metric': 'euclidean', 'n_neighbors': 4, 'wei...
8	0.788356	0.031603	{'metric': 'euclidean', 'n_neighbors': 5, 'wei...
9	0.826027	0.026385	{'metric': 'euclidean', 'n_neighbors': 5, 'wei...
10	0.773288	0.025892	{'metric': 'euclidean', 'n_neighbors': 6, 'wei...
11	0.826027	0.026207	{'metric': 'euclidean', 'n_neighbors': 6, 'wei...
12	0.764384	0.034952	{'metric': 'euclidean', 'n_neighbors': 7, 'wei...
13	0.821918	0.027906	{'metric': 'euclidean', 'n_neighbors': 7, 'wei...
14	0.758219	0.040987	{'metric': 'euclidean', 'n_neighbors': 8, 'wei...
15	0.819178	0.031566	{'metric': 'euclidean', 'n_neighbors': 8, 'wei...
16	0.746575	0.032848	{'metric': 'euclidean', 'n_neighbors': 9, 'wei...
17	0.813014	0.033562	{'metric': 'euclidean', 'n_neighbors': 9, 'wei...
18	0.743836	0.037665	{'metric': 'euclidean', 'n_neighbors': 10, 'we...
19	0.806164	0.037271	{'metric': 'euclidean', 'n_neighbors': 10, 'we...

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```

In [295]: # Applying the knn model on the resampled data using grid search for hyper parameter tuning
knn_model = KNeighborsClassifier(metric='euclidean', n_neighbors=1, weights='distance')
knn_model.fit(X_train_resampled, Y_train_resampled)

Out[295]:
KNeighborsClassifier
KNeighborsClassifier(metric='euclidean', n_neighbors=1, weights='distance')

In [296]: y_pred = knn_model.predict(X_test_resampled)

In [297]: from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
accuracy_score(Y_test_resampled, y_pred)
print(classification_report(Y_test_resampled, y_pred))

              precision    recall  f1-score   support

   drizzle         0.76         0.93         0.84         107
     fog          0.81         0.89         0.85         137
      rain         0.91         0.80         0.85         127
       snow         0.98         0.99         0.98         130
        sun         0.80         0.64         0.71         126

 accuracy          0.85
 macro avg          0.85
 weighted avg       0.86
  
```

```

In [298]: print(Y_test_resampled.value_counts())

fog      137
snow     130
  
```

In [298]: `print(Y_test_resampled.value_counts())`

```
fog      137
snow     130
rain     127
sun      126
drizzle  107
Name: weather, dtype: int64
```

In [299]: `confusion_matrix(Y_test_resampled, y_pred) #confirming that the data is balanced`

```
Out[299]: array([[100,  1,  4,  0,  2],
 [ 10, 122,  2,  0,  3],
 [  3,  4, 102,  3, 15],
 [  0,  0,  1, 129,  0],
 [ 18, 24,  3,  0, 81]])
```

Random Forest Classifier

In [300]: `!pip install -U scikit-learn`

```
Requirement already satisfied: scikit-learn in /Users/mac/opt/anaconda3/lib/python3.9/site-packages (1.4.2)
Requirement already satisfied: numpy>=1.19.5 in /Users/mac/opt/anaconda3/lib/python3.9/site-packages (from scikit-learn) (1.21.5)
Requirement already satisfied: joblib>=1.2.0 in /Users/mac/opt/anaconda3/lib/python3.9/site-packages (from scikit-learn) (1.3.2)
Requirement already satisfied: scipy>=1.6.0 in /Users/mac/opt/anaconda3/lib/python3.9/site-packages (from scikit-learn) (1.9.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in /Users/mac/opt/anaconda3/lib/python3.9/site-packages (from scikit-learn) (2.2.0)
```

Random Forest Classifier

In [300]: `!pip install -U scikit-learn`

```
Requirement already satisfied: scikit-learn in /Users/mac/opt/anaconda3/lib/python3.9/site-packages (1.4.2)
Requirement already satisfied: numpy>=1.19.5 in /Users/mac/opt/anaconda3/lib/python3.9/site-packages (from scikit-learn) (1.21.5)
Requirement already satisfied: joblib>=1.2.0 in /Users/mac/opt/anaconda3/lib/python3.9/site-packages (from scikit-learn) (1.3.2)
Requirement already satisfied: scipy>=1.6.0 in /Users/mac/opt/anaconda3/lib/python3.9/site-packages (from scikit-learn) (1.9.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in /Users/mac/opt/anaconda3/lib/python3.9/site-packages (from scikit-learn) (2.2.0)
Note: you may need to restart the kernel to use updated packages.
```

In [301]: `from sklearn.ensemble import RandomForestClassifier #importing random forest classifier`
`from sklearn import metrics`

In [302]: `#creating a random forest classifier`
`rfc = RandomForestClassifier()`
`forest_params = [{'max_depth': list(range(10, 15)), 'max_features': list(range(1,14))}]`
`clf = GridSearchCV(rfc, forest_params, cv = 10, scoring='accuracy')`
`y_pred_rfc = clf.fit(X_train_resampled, Y_train_resampled)`
`# Get the best estimator from the grid search`
`best_rfc = clf.best_estimator_`

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```

clf = GridSearchCV(rfc, forest_params, cv = 10, scoring='accuracy')
y_pred_rfc = clf.fit(X_train_resampled, Y_train_resampled)

# Get the best estimator from the grid search
best_rfc = clf.best_estimator_

# Make predictions using the best estimator
y_pred_best_rfc = best_rfc.predict(X_test_resampled)

# Print the best parameters and score
print(clf.best_params_)
print(clf.best_score_)

# Print the classification report using the actual predictions
print(classification_report(Y_test_resampled, y_pred_best_rfc))

{'max_depth': 13, 'max_features': 2}
0.8760273972602739

```

	precision	recall	f1-score	support
drizzle	0.74	0.94	0.83	107
fog	0.82	0.85	0.84	137
rain	0.97	0.92	0.94	127
snow	0.98	0.98	0.98	130
sun	0.82	0.63	0.71	126
accuracy			0.86	627
macro avg	0.86	0.86	0.86	627
weighted avg	0.87	0.86	0.86	627

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GRADIENT BOOSTING CLASSIFIER

```

In [303]: #Gradient-Boosting Classifier
!pip install -U scikit-learn
from sklearn.ensemble import GradientBoostingClassifier

Requirement already satisfied: scikit-learn in /Users/mac/opt/anaconda3/lib/python3.9/site-packages (1.4.2)
Requirement already satisfied: scipy>=1.6.0 in /Users/mac/opt/anaconda3/lib/python3.9/site-packages (from scikit-learn) (1.9.1)
Requirement already satisfied: numpy>=1.19.5 in /Users/mac/opt/anaconda3/lib/python3.9/site-packages (from scikit-learn) (1.21.5)
Requirement already satisfied: threadpoolctl>=2.0.0 in /Users/mac/opt/anaconda3/lib/python3.9/site-packages (from scikit-learn) (2.2.0)
Requirement already satisfied: joblib>=1.2.0 in /Users/mac/opt/anaconda3/lib/python3.9/site-packages (from scikit-learn) (1.3.2)
Note: you may need to restart the kernel to use updated packages.

```

```

In [ ]: #creating the gradient boosting classifier

```

```

In [304]: gbc=GradientBoostingClassifier(n_estimators=500,learning_rate=0.05,random_state=100,max_features=5)
gbc.fit(X_train_resampled,Y_train_resampled)

# Generate predictions using the fitted model
y_pred_gbc = gbc.predict(X_test_resampled)

print("GBC accuracy is %2.2f" % accuracy_score(Y_test_resampled, y_pred_gbc))
print(classification_report(Y_test_resampled, y_pred_gbc))

GBC accuracy is 0.87

```

	precision	recall	f1-score	support
drizzle	0.74	0.94	0.83	107
fog	0.82	0.85	0.84	137
rain	0.97	0.92	0.94	127
snow	0.98	0.98	0.98	130
sun	0.82	0.63	0.71	126
accuracy			0.86	627
macro avg	0.86	0.86	0.86	627
weighted avg	0.87	0.86	0.86	627

```
In [304]: gbc=GradientBoostingClassifier(n_estimators=500, learning_rate=0.05, random_state=100, max_features=5)
gbc.fit(X_train_resampled, Y_train_resampled)

# Generate predictions using the fitted model
y_pred_gbc = gbc.predict(X_test_resampled)

print("GBC accuracy is %2.2f" % accuracy_score(Y_test_resampled, y_pred_gbc))
print(classification_report(Y_test_resampled, y_pred_gbc))
```

GBC accuracy is 0.87

	precision	recall	f1-score	support
drizzle	0.81	0.85	0.83	107
fog	0.81	0.82	0.82	137
rain	0.94	0.93	0.93	127
snow	0.98	0.98	0.98	130
sun	0.80	0.75	0.78	126
accuracy			0.87	627
macro avg	0.87	0.87	0.87	627
weighted avg	0.87	0.87	0.87	627

Naive Bayes Classification

```
In [305]: from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score
```

Naive Bayes Classification

```
In [305]: from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score
```

```
In [306]: #creating and evaluating the GNB classifier
gnb = GaussianNB()
y_pred = gnb.fit(X_train_resampled, Y_train_resampled).predict(X_test_resampled)
print("Number of mislabeled points out of a total %d points : %d" % (X_test.shape[0], (Y_test_resampled != y_pred).sum()))
```

Number of mislabeled points out of a total 439 points : 230

```
In [307]: from sklearn.metrics import accuracy_score

#We run the model on the train data

# Here we train the model using the resampled training data
gnb.fit(X_train_resampled, Y_train_resampled)

# then proceed to make predictions on the training data
predict_train = gnb.predict(X_train_resampled)

# before evaluating the accuracy on the training data
accuracy_train = accuracy_score(Y_train_resampled, predict_train)
print('accuracy_score on train dataset: ', accuracy_train)
```

accuracy_score on train dataset: 0.6267123287671232

```
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```

```
In [308]: #we run the model on the test data
# then proceed to make predictions on the training data
# predict the target on the test dataset
predict_test = gnb.predict(X_test_resampled)

# Accuracy Score on test dataset
accuracy_test = accuracy_score(Y_test_resampled, predict_test)
print('accuracy_score on test dataset : ', accuracy_test)
print(classification_report(Y_test_resampled, y_pred))

accuracy_score on test dataset : 0.6331738437001595
precision    recall    f1-score   support

   drizzle    0.38    0.41    0.40     107
     fog    0.40    0.47    0.43     137
    rain    0.97    0.85    0.91     127
    snow    0.91    0.98    0.94     130
     sun    0.54    0.43    0.48     126

 accuracy          0.63
macro avg          0.64
weighted avg       0.65
```

```
In [ ]:
```

```
In [309]: # check for overfitting
print('Training score: {0:0.4f}'.format(gnb.score(X_train_resampled, Y_train_resampled)))
print('Testing score: {0:0.4f}'.format(gnb.score(X_test_resampled, Y_test_resampled)))

Training score: 0.6267
Testing score: 0.6332
```

```
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```

SUPPORT VECTOR MACHINE

```
In [310]: from sklearn.svm import SVC
svc = SVC()
svc.fit(X_train_resampled, Y_train_resampled)
# print prediction results
predictions = svc.predict(X_test_resampled)
print(classification_report(Y_test_resampled, predictions))

print("Accuracy on training set: {:.3f}".format(svc.score(X_train_resampled, Y_train_resampled)))
print("Accuracy on test set: {:.3f}".format(svc.score(X_test_resampled, Y_test_resampled)))

precision    recall    f1-score   support

   drizzle    0.55    0.25    0.35     107
     fog    0.42    0.79    0.55     137
    rain    0.95    0.72    0.82     127
    snow    0.95    0.95    0.95     130
     sun    0.54    0.40    0.46     126

 accuracy          0.64
macro avg          0.68
weighted avg       0.68

Accuracy on training set: 0.645
Accuracy on test set: 0.638
```

```
In [311]: #apply grid search to find the best parameter combination
from sklearn.model_selection import GridSearchCV

# defining parameter range
param_grid = {'C': [0.1, 1, 10, 100, 1000]
```

```
In [311]: #apply grid search to find the best parameter combination
from sklearn.model_selection import GridSearchCV

# defining parameter range
param_grid = {'C': [0.1, 1, 10, 100, 1000],
              'gamma': [1, 0.1, 0.01, 0.001, 0.0001],
              'kernel': ['rbf']}

grid = GridSearchCV(SVC(), param_grid, refit = True, verbose = 3)

# fitting the model for grid search
grid.fit(X_train_resampled, Y_train_resampled)

# print best parameter after tuning
print(grid.best_params_)

# print how our model looks after hyper-parameter tuning
print(grid.best_estimator_)
```

```
[CV 2/5] END .....C=0.1, gamma=1, kernel=rbf;; score=0.503 total time= 0.2s
[CV 3/5] END .....C=0.1, gamma=1, kernel=rbf;; score=0.476 total time= 0.2s
[CV 4/5] END .....C=0.1, gamma=1, kernel=rbf;; score=0.558 total time= 0.2s
[CV 5/5] END .....C=0.1, gamma=1, kernel=rbf;; score=0.459 total time= 0.2s
[CV 1/5] END .....C=0.1, gamma=0.1, kernel=rbf;; score=0.668 total time= 0.1s
[CV 2/5] END .....C=0.1, gamma=0.1, kernel=rbf;; score=0.702 total time= 0.1s
[CV 3/5] END .....C=0.1, gamma=0.1, kernel=rbf;; score=0.702 total time= 0.1s
[CV 4/5] END .....C=0.1, gamma=0.1, kernel=rbf;; score=0.634 total time= 0.1s
[CV 5/5] END .....C=0.1, gamma=0.1, kernel=rbf;; score=0.661 total time= 0.1s
[CV 1/5] END .....C=0.1, gamma=0.01, kernel=rbf;; score=0.568 total time= 0.1s
[CV 2/5] END .....C=0.1, gamma=0.01, kernel=rbf;; score=0.558 total time= 0.1s
[CV 3/5] END .....C=0.1, gamma=0.01, kernel=rbf;; score=0.562 total time= 0.1s
[CV 4/5] END .....C=0.1, gamma=0.01, kernel=rbf;; score=0.534 total time= 0.1s
[CV 5/5] END .....C=0.1, gamma=0.01, kernel=rbf;; score=0.623 total time= 0.1s
```

```
[CV 4/5] END ...C=1000, gamma=0.001, kernel=rbf;; score=0.675 total time= 0.2s
[CV 5/5] END ...C=1000, gamma=0.001, kernel=rbf;; score=0.709 total time= 0.2s
[CV 1/5] END ..C=1000, gamma=0.0001, kernel=rbf;; score=0.695 total time= 0.1s
[CV 2/5] END ..C=1000, gamma=0.0001, kernel=rbf;; score=0.682 total time= 0.1s
[CV 3/5] END ..C=1000, gamma=0.0001, kernel=rbf;; score=0.640 total time= 0.1s
[CV 4/5] END ..C=1000, gamma=0.0001, kernel=rbf;; score=0.582 total time= 0.1s
[CV 5/5] END ..C=1000, gamma=0.0001, kernel=rbf;; score=0.664 total time= 0.1s
{'C': 1000, 'gamma': 0.1, 'kernel': 'rbf'}
SVC(C=1000, gamma=0.1)
```

```
In [312]: grid_predictions = grid.predict(X_test_resampled)

# print classification report
print(classification_report(Y_test_resampled, grid_predictions))
```

	precision	recall	f1-score	support
drizzle	0.75	0.96	0.84	107
fog	0.83	0.91	0.86	137
rain	0.93	0.85	0.89	127
snow	0.98	0.99	0.98	130
sun	0.82	0.60	0.69	126
accuracy			0.86	627
macro avg	0.86	0.86	0.85	627
weighted avg	0.86	0.86	0.86	627

```
In [313]: #print accuracy score after grid search tuning
print(accuracy_score(Y_test_resampled, grid_predictions)*100)

85.96491228070175
```



```
In [314]: import matplotlib.pyplot as plt

# Calculate accuracy for each model
knn_accuracy = accuracy_score(Y_test_resampled, knn_model.predict(X_test_resampled))
rf_accuracy = accuracy_score(Y_test_resampled, clf.predict(X_test_resampled))
gbc_accuracy = accuracy_score(Y_test_resampled, gbc.predict(X_test_resampled))
gnb_accuracy = accuracy_score(Y_test_resampled, gnb.predict(X_test_resampled))
svm_accuracy = accuracy_score(Y_test_resampled, svc.predict(X_test_resampled))

# Define the models and their corresponding accuracy scores
models = ['KNN', 'Random Forest', 'Gradient Boosting', 'Naive Bayes', 'SVM']
accuracies = [knn_accuracy, rf_accuracy, gbc_accuracy, gnb_accuracy, svm_accuracy]

# Plot the bar plot
plt.figure(figsize=(10, 6))
plt.bar(models, accuracies, color='skyblue')
plt.xlabel('Model')
plt.ylabel('Accuracy')
plt.title('Accuracy of Different Models')
plt.ylim(0.5, 1.0) # Adjust ylim if necessary
plt.xticks(rotation=45) # Rotate x-axis labels for better readability
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```

