MINOR PROJECT | ETMN100

Flood Prediction Model

In [59]:

```
#Basic libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

Gather data to preprocess the training and validation data

In [60]:

```
# Load training/validation data
trainval_data = pd.read_csv('train.csv')
```

In [61]:

```
trainval_data.head()
```

Out[61]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OC
0	ANDAMAN & NICOBAR ISLANDS	1901	49.2	87.1	29.2	2.3	528.8	517.5	365.1	481.1	332.6	388
1	ANDAMAN & NICOBAR ISLANDS	1902	0.0	159.8	12.2	0.0	446.1	537.1	228.9	753.7	666.2	197
2	ANDAMAN & NICOBAR ISLANDS	1903	12.7	144.0	0.0	1.0	235.1	479.9	728.4	326.7	339.0	181
3	ANDAMAN & NICOBAR ISLANDS	1904	9.4	14.7	0.0	202.4	304.5	495.1	502.0	160.1	820.4	222
4	ANDAMAN & NICOBAR ISLANDS	1905	1.3	0.0	3.3	26.9	279.5	628.7	368.7	330.5	297.0	260

In [62]:

```
#Check for any colomns is left empty
trainval_data.apply(lambda x:sum(x.isnull()), axis=0)
```

Out[62]:

```
SUBDIVISION    0
YEAR           0
JAN            0
FEB            0
MAR            0
APR            0
MAY            0
JUN            0
JUL            0
AUG            0
SEP            0
OCT            0
NOV            0
DEC            0
ANNUAL         0
Flood          0
dtype: int64
```

In [63]:

```
#The data is required in numbers, therefore replace the yes/no in flood:
trainval_data['Flood'].replace(['Yes','No'],[1,0],inplace=True)
```

In [64]:

```
trainval_data.head()
```

Out[64]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OC
0	ANDAMAN & NICOBAR ISLANDS	1901	49.2	87.1	29.2	2.3	528.8	517.5	365.1	481.1	332.6	388
1	ANDAMAN & NICOBAR ISLANDS	1902	0.0	159.8	12.2	0.0	446.1	537.1	228.9	753.7	666.2	197
2	ANDAMAN & NICOBAR ISLANDS	1903	12.7	144.0	0.0	1.0	235.1	479.9	728.4	326.7	339.0	181
3	ANDAMAN & NICOBAR ISLANDS	1904	9.4	14.7	0.0	202.4	304.5	495.1	502.0	160.1	820.4	222
4	ANDAMAN & NICOBAR ISLANDS	1905	1.3	0.0	3.3	26.9	279.5	628.7	368.7	330.5	297.0	260

In [65]:

```
from sklearn.preprocessing import LabelEncoder
# Assuming 'SUBDIVISION' is the column name in your dataset
label_encoder = LabelEncoder()
trainval_data['subdivision_encoded'] = label_encoder.fit_transform(trai
```

In [66]:

```
trainval_data.head(10)
```

Out[66]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP
0	ANDAMAN & NICOBAR ISLANDS	1901	49.2	87.1	29.2	2.3	528.8	517.5	365.1	481.1	332.6
1	ANDAMAN & NICOBAR ISLANDS	1902	0.0	159.8	12.2	0.0	446.1	537.1	228.9	753.7	666.2
2	ANDAMAN & NICOBAR ISLANDS	1903	12.7	144.0	0.0	1.0	235.1	479.9	728.4	326.7	339.0
3	ANDAMAN & NICOBAR ISLANDS	1904	9.4	14.7	0.0	202.4	304.5	495.1	502.0	160.1	820.4
4	ANDAMAN & NICOBAR ISLANDS	1905	1.3	0.0	3.3	26.9	279.5	628.7	368.7	330.5	297.0
5	ANDAMAN & NICOBAR ISLANDS	1906	36.6	0.0	0.0	0.0	556.1	733.3	247.7	320.5	164.3
6	ANDAMAN & NICOBAR ISLANDS	1907	110.7	0.0	113.3	21.6	616.3	305.2	443.9	377.6	200.4
7	ANDAMAN & NICOBAR ISLANDS	1908	20.9	85.1	0.0	29.0	562.0	693.6	481.4	699.9	428.8
8	ANDAMAN & NICOBAR ISLANDS	1910	26.6	22.7	206.3	89.3	224.5	472.7	264.3	337.4	626.6
9	ANDAMAN & NICOBAR ISLANDS	1911	0.0	8.4	0.0	122.5	327.3	649.0	253.0	187.1	464.5

In [67]:
```
#moving the encoded subdivision column infront to easily separate targe
column_order = ['subdivision_encoded', 'SUBDIVISION', 'YEAR', 'JAN', 'F
# Rearrange columns based on 'column_order'
trainval_data = trainval_data[column_order]
trainval_data.head()
```

Out[67]:

	subdivision_encoded	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	.
0	0	ANDAMAN & NICOBAR ISLANDS	1901	49.2	87.1	29.2	2.3	528.8	517.5	36
1	0	ANDAMAN & NICOBAR ISLANDS	1902	0.0	159.8	12.2	0.0	446.1	537.1	22
2	0	ANDAMAN & NICOBAR ISLANDS	1903	12.7	144.0	0.0	1.0	235.1	479.9	72
3	0	ANDAMAN & NICOBAR ISLANDS	1904	9.4	14.7	0.0	202.4	304.5	495.1	5(
4	0	ANDAMAN & NICOBAR ISLANDS	1905	1.3	0.0	3.3	26.9	279.5	628.7	36

In [68]:
```
trainval_data.drop('SUBDIVISION', axis=1, inplace=True)
```

In [69]:
```
#Seperate the data for prediction
X = trainval_data.iloc[:,0:15]
X.head()
```

Out[69]:

	subdivision_encoded	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SI
0	0	1901	49.2	87.1	29.2	2.3	528.8	517.5	365.1	481.1	33
1	0	1902	0.0	159.8	12.2	0.0	446.1	537.1	228.9	753.7	66
2	0	1903	12.7	144.0	0.0	1.0	235.1	479.9	728.4	326.7	33
3	0	1904	9.4	14.7	0.0	202.4	304.5	495.1	502.0	160.1	82
4	0	1905	1.3	0.0	3.3	26.9	279.5	628.7	368.7	330.5	29

Preprocessing the test dataset

In [70]:
```
# Load testing data
test_data = pd.read_csv('maintest.csv')
```

In [71]:
```
test_data.head()
```

Out[71]:

	SUBDIVISIONS	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	C
0	ANDAMAN & NICOBAR ISLANDS	2019	173.8	5.8	15.8	35.3	230.9	662.2	212.0	860.4	596.8	13
1	ANDAMAN & NICOBAR ISLANDS	2021	42.7	48.8	38.3	150.2	414.1	315.9	535.3	506.5	667.3	41
2	ANDAMAN & NICOBAR ISLANDS	2016	72.0	15.8	5.4	2.4	191.1	429.4	301.2	227.7	604.3	28
3	ANDAMAN & NICOBAR ISLANDS	2017	228.7	5.6	33.0	108.3	275.8	349.1	389.4	414.7	372.8	26
4	ANDAMAN & NICOBAR ISLANDS	2018	167.3	36.2	21.5	90.0	372.5	518.4	239.1	415.7	395.9	29

In [72]:
```
#Check for any colomns is left empty
test_data.apply(lambda x:sum(x.isnull()), axis=0)
```

Out[72]:
```
SUBDIVISIONS    0
YEAR            0
JAN             0
FEB             0
MAR             0
APR             0
MAY             0
JUN             0
JUL             0
AUG             0
SEP             0
OCT             0
NOV             0
DEC             0
ANNUAL          0
FLOOD           0
dtype: int64
```

In [73]:
```
#The data is required in numbers, therefore replace the yes/no in floods
test_data['FLOOD'].replace(['YES','NO'],[1,0],inplace=True)
```

In [74]:
```
test_data.head()
```

Out[74]:

	SUBDIVISIONS	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	C
0	ANDAMAN & NICOBAR ISLANDS	2019	173.8	5.8	15.8	35.3	230.9	662.2	212.0	860.4	596.8	13
1	ANDAMAN & NICOBAR ISLANDS	2021	42.7	48.8	38.3	150.2	414.1	315.9	535.3	506.5	667.3	41
2	ANDAMAN & NICOBAR ISLANDS	2016	72.0	15.8	5.4	2.4	191.1	429.4	301.2	227.7	604.3	28
3	ANDAMAN & NICOBAR ISLANDS	2017	228.7	5.6	33.0	108.3	275.8	349.1	389.4	414.7	372.8	26
4	ANDAMAN & NICOBAR ISLANDS	2018	167.3	36.2	21.5	90.0	372.5	518.4	239.1	415.7	395.9	29

In [75]:
```
#encoding string to integer
label_encoder = LabelEncoder()
test_data['subdivision_encoded'] = label_encoder.fit_transform(test_dat
```

In [76]:

```
test_data.head(10)
```

Out[76]:

	SUBDIVISIONS	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	
0	ANDAMAN & NICOBAR ISLANDS	2019	173.8	5.8	15.8	35.3	230.9	662.2	212.0	860.4	596.8	1
1	ANDAMAN & NICOBAR ISLANDS	2021	42.7	48.8	38.3	150.2	414.1	315.9	535.3	506.5	667.3	4
2	ANDAMAN & NICOBAR ISLANDS	2016	72.0	15.8	5.4	2.4	191.1	429.4	301.2	227.7	604.3	2
3	ANDAMAN & NICOBAR ISLANDS	2017	228.7	5.6	33.0	108.3	275.8	349.1	389.4	414.7	372.8	2
4	ANDAMAN & NICOBAR ISLANDS	2018	167.3	36.2	21.5	90.0	372.5	518.4	239.1	415.7	395.9	2
5	ANDHRA PRADESH	2017	2.2	0.0	12.5	8.8	34.7	124.1	110.8	202.1	164.0	1
6	ANDHRA PRADESH	2018	0.1	2.0	16.7	24.9	51.7	90.5	117.1	141.3	97.7	[illegible]
7	ARUNACHAL PRADESH	2016	29.4	73.2	128.4	333.1	278.9	379.4	620.1	145.7	532.9	1
8	ARUNACHAL PRADESH	2017	8.2	86.2	221.8	348.2	257.1	370.8	437.8	456.4	318.6	2
9	ARUNACHAL PRADESH	2018	30.9	67.7	139.5	150.7	269.9	320.7	341.7	247.3	288.8	[illegible]

In [77]:

```
#moving the encoded subdivision column infront to easily separate targe
column_order = ['subdivision_encoded', 'SUBDIVISIONS', 'YEAR', 'JAN', '
# Rearrange columns based on 'column_order'
test_data = test_data[column_order]
test_data.head()
```

Out[77]:

	subdivision_encoded	SUBDIVISIONS	YEAR	JAN	FEB	MAR	APR	MAY	JUN
0	1	ANDAMAN & NICOBAR ISLANDS	2019	173.8	5.8	15.8	35.3	230.9	662.2
1	1	ANDAMAN & NICOBAR ISLANDS	2021	42.7	48.8	38.3	150.2	414.1	315.9
2	1	ANDAMAN & NICOBAR ISLANDS	2016	72.0	15.8	5.4	2.4	191.1	429.4
3	1	ANDAMAN & NICOBAR ISLANDS	2017	228.7	5.6	33.0	108.3	275.8	349.1
4	1	ANDAMAN & NICOBAR ISLANDS	2018	167.3	36.2	21.5	90.0	372.5	518.4

In [78]:

```
test_data.drop('SUBDIVISIONS', axis=1, inplace=True)
```

In [79]:

```
test_data.head(10)
```

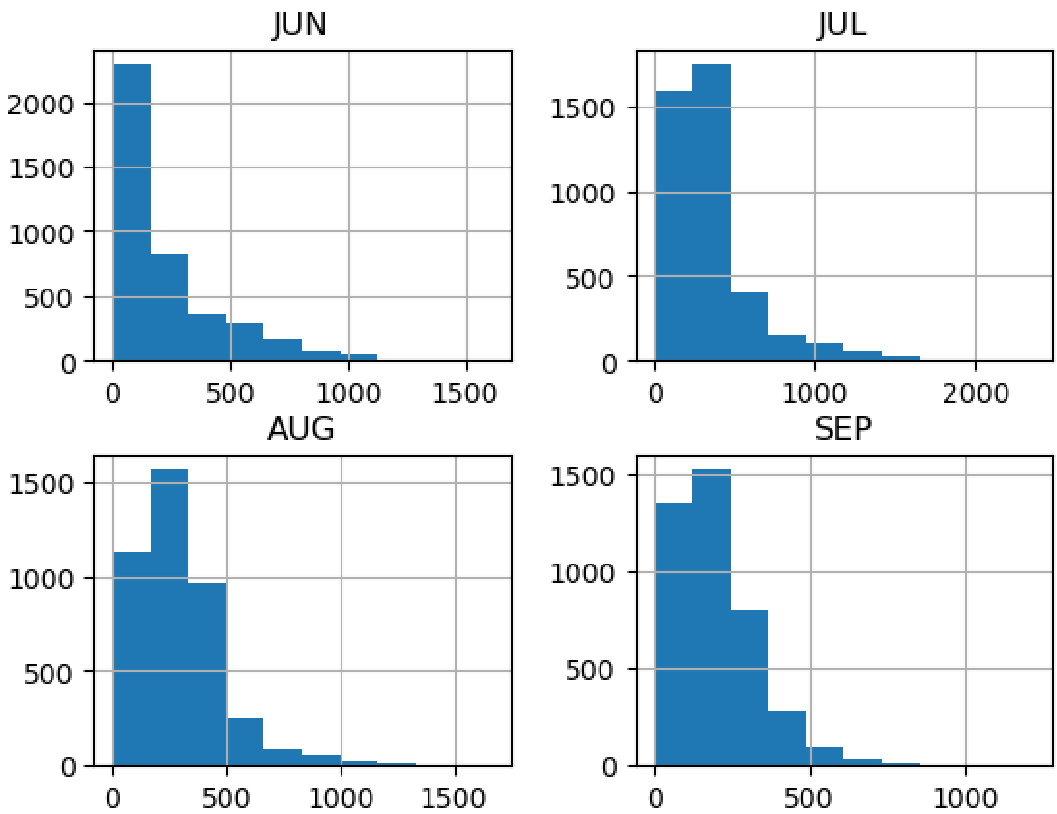
Out[79]:

	subdivision_encoded	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	S
0	1	2019	173.8	5.8	15.8	35.3	230.9	662.2	212.0	860.4	59
1	1	2021	42.7	48.8	38.3	150.2	414.1	315.9	535.3	506.5	66
2	1	2016	72.0	15.8	5.4	2.4	191.1	429.4	301.2	227.7	60
3	1	2017	228.7	5.6	33.0	108.3	275.8	349.1	389.4	414.7	37
4	1	2018	167.3	36.2	21.5	90.0	372.5	518.4	239.1	415.7	39
5	2	2017	2.2	0.0	12.5	8.8	34.7	124.1	110.8	202.1	16
6	2	2018	0.1	2.0	16.7	24.9	51.7	90.5	117.1	141.3	9
7	3	2016	29.4	73.2	128.4	333.1	278.9	379.4	620.1	145.7	53
8	3	2017	8.2	86.2	221.8	348.2	257.1	370.8	437.8	456.4	31
9	3	2018	30.9	67.7	139.5	150.7	269.9	320.7	341.7	247.3	28

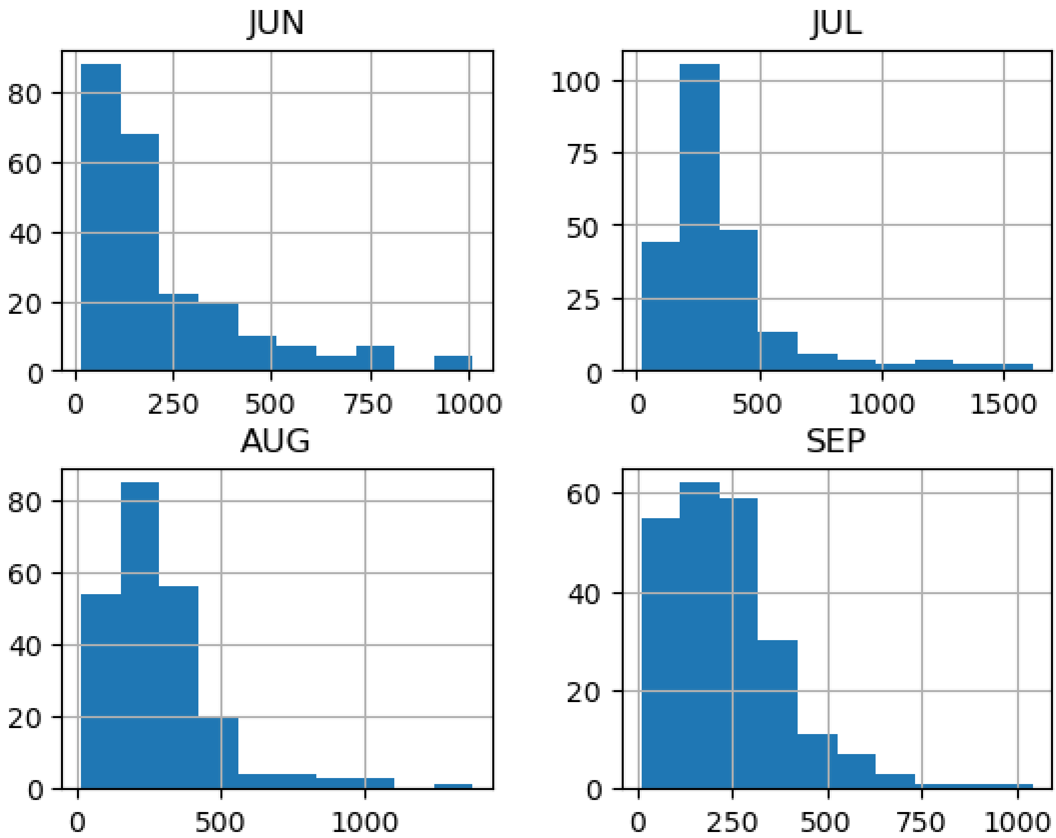
EDA

In [80]:

```
#Explore how rainfall index varies during rainy season for trainval_data
%matplotlib inline
c = trainval_data[['JUN','JUL','AUG','SEP']]
c.hist()
plt.show()
```



In [81]:
```
#Explore how rainfall index varies during rainy season for test dataset
%matplotlib inline
c = test_data[['JUN','JUL','AUG','SEP']]
c.hist()
plt.show()
```



In [82]:
```
#Data might be widely distributed so let's scale it between 0 and 1
from sklearn import preprocessing
minmax = preprocessing.MinMaxScaler(feature_range=(0,1))
minmax.fit(X).transform(X)
```

Out[82]:
```
array([[0.        , 0.        , 0.08428987, ..., 0.860225  , 0.0544129
6,
         0.52815531],
       [0.        , 0.00877193, 0.        , ..., 0.55324395, 0.2599190
3,
         0.55168453],
       [0.        , 0.01754386, 0.02175775, ..., 0.43828017, 0.3643724
7,
         0.46182682],
       ...,
       [0.51428571, 0.98245614, 0.04488607, ..., 0.12035753, 0.0432388
7,
         0.2175855 ],
       [0.51428571, 0.99122807, 0.09114271, ..., 0.0909231 , 0.1008906
9,
         0.21259252],
       [0.51428571, 1.        , 0.00376906, ..., 0.35598706, 0.2574898
8,
         0.25213757]])
```

Flood Prediction Algorithms

1. KNN Classifier

In [83]:

```
from sklearn.model_selection import train_test_split

# Split the training+validation data into training (80%) and validation
X_trainval, X_val, y_trainval, y_val = train_test_split(
    trainval_data.drop('Flood', axis=1),  # Features
    trainval_data['Flood'],  # Target variable
    test_size=0.2,  # Validation size
    random_state=42
)

# Remaining training data after splitting
X_train, y_train = X_trainval, y_trainval
```

In [84]:

```
#Train and validate
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report
# Initialize KNN model
knn = KNeighborsClassifier(n_neighbors=5)  # You can adjust the number 

# Train the model on the training data
knn.fit(X_train, y_train)

# Predict on the validation set
y_pred_val = knn.predict(X_val)
```

In [85]:

```
# Evaluate performance on validation set
accuracy_val = accuracy_score(y_val, y_pred_val)
print("Validation Accuracy:", accuracy_val)
# Additional evaluation metrics or reports for validation set
report_val = classification_report(y_val, y_pred_val)
print("Validation Classification Report:\n", report_val)
```

```
Validation Accuracy: 0.9902200488997555
Validation Classification Report:
               precision    recall  f1-score   support

           0       0.99      1.00      0.99       751
           1       0.97      0.91      0.94        67

    accuracy                           0.99       818
   macro avg       0.98      0.95      0.97       818
weighted avg       0.99      0.99      0.99       818
```

In [86]:
```
# Test the trained model on the separate test set
# Separate test data
X_test, y_test = test_data.drop('FLOOD', axis=1), test_data['FLOOD']

# Predict on the test set
y_pred_test = knn.predict(X_test)
# Evaluate performance on the test set
accuracy_test = accuracy_score(y_test, y_pred_test)
print("Test Accuracy:", accuracy_test)
# Additional evaluation metrics or reports for test set
report_test = classification_report(y_test, y_pred_test)
print("Test Classification Report:\n", report_test)
```

```
Test Accuracy: 0.991304347826087
Test Classification Report:
               precision    recall  f1-score   support

           0       0.99      1.00      1.00       210
           1       1.00      0.90      0.95        20

    accuracy                           0.99       230
   macro avg       1.00      0.95      0.97       230
weighted avg       0.99      0.99      0.99       230
```

2. Logistic Regression

In [87]:
```
from sklearn.linear_model import LogisticRegression
```

In [88]:
```
# Initialize Logistic Regression classifier
log_reg = LogisticRegression(max_iter=1000)

# Train the model on the training data
log_reg.fit(X_train, y_train)

# Predict on the validation set
y_pred_val_log_reg = log_reg.predict(X_val)
```

In [89]:
```
# Evaluate performance on validation set
accuracy_val_log_reg = accuracy_score(y_val, y_pred_val_log_reg)
print("Validation Accuracy:", accuracy_val_log_reg)
# Additional evaluation metrics or reports for validation set
report_val_log_reg = classification_report(y_val, y_pred_val_log_reg)
print("Validation Classification Report:\n", report_val_log_reg)
```

```
Validation Accuracy: 0.9926650366748166
Validation Classification Report:
               precision    recall  f1-score   support

           0       1.00      0.99      1.00       751
           1       0.93      0.99      0.96        67

    accuracy                           0.99       818
   macro avg       0.96      0.99      0.98       818
weighted avg       0.99      0.99      0.99       818
```

In [90]:
```
# Test the trained model on the separate test set
y_pred_test_log_reg = log_reg.predict(X_test)
# Evaluate performance on the test set
accuracy_test_log_reg = accuracy_score(y_test, y_pred_test_log_reg)
print("Test Accuracy:", accuracy_test)
# Additional evaluation metrics or reports for test set
report_test_log_reg = classification_report(y_test, y_pred_test_log_reg
print("Test Classification Report:\n", report_test_log_reg)
```

```
Test Accuracy: 0.991304347826087
Test Classification Report:
              precision    recall  f1-score   support

           0       0.99      1.00      1.00       210
           1       1.00      0.90      0.95        20

    accuracy                           0.99       230
   macro avg       1.00      0.95      0.97       230
weighted avg       0.99      0.99      0.99       230
```

2. Decision Tree Classifier

In [91]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [92]:
```
# Initialize Decision Tree Classifier
decision_tree = DecisionTreeClassifier(random_state=42)

# Train the model on the training set
decision_tree.fit(X_train, y_train)
# Validate on the validation set
y_pred_val_dec_tre = decision_tree.predict(X_val)
```

In [93]:
```
# Evaluate performance on validation set
accuracy__dec_tre = accuracy_score(y_val, y_pred_val_dec_tre)
print("Validation Accuracy:", accuracy__dec_tre)
# Additional evaluation metrics or reports for validation set
report__dec_tre = classification_report(y_val, y_pred_val_dec_tre)
print("Validation Classification Report:\n", report__dec_tre)
```

```
Validation Accuracy: 1.0
Validation Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       751
           1       1.00      1.00      1.00        67

    accuracy                           1.00       818
   macro avg       1.00      1.00      1.00       818
weighted avg       1.00      1.00      1.00       818
```

In [94]:

```
# Test the trained model on the separate test set
y_pred_test_dec_tre = decision_tree.predict(X_test)
# Evaluate performance on the test set
accuracy_dec_tre = accuracy_score(y_test, y_pred_test_dec_tre)
print("Test Accuracy:", accuracy_dec_tre)
# Additional evaluation metrics or reports for test set
report_dec_tre = classification_report(y_test, y_pred_test_dec_tre)
print("Test Classification Report:\n", report_dec_tre)
```

```
Test Accuracy: 1.0
Test Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       210
           1       1.00      1.00      1.00        20

    accuracy                           1.00       230
   macro avg       1.00      1.00      1.00       230
weighted avg       1.00      1.00      1.00       230
```

4. Random Forest Classifier

In [95]:

```
from sklearn.ensemble import RandomForestClassifier
# Initialize Random Forest Classifier
random_forest = RandomForestClassifier(random_state=42) # You can set o
# Train the model on the training set
random_forest.fit(X_train, y_train)
# Validate on the validation set
y_pred_val_ran_for = random_forest.predict(X_val)
```

In [96]:

```
# Evaluate performance on validation set
accuracy_ran_for = accuracy_score(y_val, y_pred_val_ran_for)
print("Validation Accuracy:", accuracy_ran_for)
# Additional evaluation metrics or reports for validation set
report_ran_for = classification_report(y_val, y_pred_val_ran_for)
print("Validation Classification Report:\n", report_ran_for)
```

```
Validation Accuracy: 1.0
Validation Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       751
           1       1.00      1.00      1.00        67

    accuracy                           1.00       818
   macro avg       1.00      1.00      1.00       818
weighted avg       1.00      1.00      1.00       818
```

In [97]:
```
# Test the trained model on the separate test set
y_pred_test_ran_for = random_forest.predict(X_test)
# Evaluate performance on the test set
accuracy_ran_for = accuracy_score(y_test, y_pred_test_ran_for)
print("Test Accuracy:", accuracy_ran_for)
# Additional evaluation metrics or reports for test set
report_ran_for = classification_report(y_test, y_pred_test_ran_for)
print("Test Classification Report:\n", report_ran_for)
```

```
Test Accuracy: 1.0
Test Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       210
           1       1.00      1.00      1.00        20

    accuracy                           1.00       230
   macro avg       1.00      1.00      1.00       230
weighted avg       1.00      1.00      1.00       230
```

5. SVM

In [98]:
```
from sklearn.svm import SVC
svm_model = SVC(kernel='linear', C=1.0)  # Example with a linear kernel
svm_model.fit(X_train, y_train)

# Predict on the validation set
y_pred_val_svm = svm_model.predict(X_val)
```

In [99]:
```
# Evaluate performance on validation set
accuracy_val_svm = accuracy_score(y_val, y_pred_val_svm)
print("Validation Accuracy:", accuracy_val_svm)
# Additional evaluation metrics or reports for validation set
report_val_svm = classification_report(y_val, y_pred_val_svm)
print("Validation Classification Report:\n", report_val_svm)
```

```
Validation Accuracy: 1.0
Validation Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       751
           1       1.00      1.00      1.00        67

    accuracy                           1.00       818
   macro avg       1.00      1.00      1.00       818
weighted avg       1.00      1.00      1.00       818
```

In [100]:

```
# Test the trained model on the separate test set
y_pred_test_svm = svm_model.predict(X_test)
# Evaluate performance on the test set
accuracy_test_svm = accuracy_score(y_test, y_pred_test_svm)
print("Test Accuracy:", accuracy_test_svm)
# Additional evaluation metrics or reports for test set
report_test_svm = classification_report(y_test, y_pred_test_svm)
print("Test Classification Report:\n", report_test_svm)
```

```
Test Accuracy: 1.0
Test Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       210
           1       1.00      1.00      1.00        20

    accuracy                           1.00       230
   macro avg       1.00      1.00      1.00       230
weighted avg       1.00      1.00      1.00       230
```

6. Naive Bayes

In [101]:

```
from sklearn.naive_bayes import GaussianNB
```

In [102]:

```
naive_bayes_model = GaussianNB()
naive_bayes_model.fit(X_train, y_train)

# Predict on the validation set
y_pred_val_nb = naive_bayes_model.predict(X_val)
```

In [103]:

```
# Evaluate performance on validation set
accuracy_val_nb = accuracy_score(y_val, y_pred_val_nb)
print("Validation Accuracy:", accuracy_val_nb)
# Additional evaluation metrics or reports for validation set
report_val_nb = classification_report(y_val, y_pred_val_nb)
print("Validation Classification Report:\n", report_val_nb)
```

```
Validation Accuracy: 0.8936430317848411
Validation Classification Report:
               precision    recall  f1-score   support

           0       1.00      0.88      0.94       751
           1       0.44      1.00      0.61        67

    accuracy                           0.89       818
   macro avg       0.72      0.94      0.77       818
weighted avg       0.95      0.89      0.91       818
```

In [104]:
```
# Test the trained model on the separate test set
y_pred_test_nb = naive_bayes_model.predict(X_test)
# Evaluate performance on the test set
accuracy_test_nb = accuracy_score(y_test, y_pred_test_nb)
print("Test Accuracy:", accuracy_test_nb)
# Additional evaluation metrics or reports for test set
report_test_nb = classification_report(y_test, y_pred_test_nb)
print("Test Classification Report:\n", report_test_nb)
```

```
Test Accuracy: 0.9478260869565217
Test Classification Report:
               precision    recall  f1-score   support

           0       1.00      0.94      0.97       210
           1       0.62      1.00      0.77        20

    accuracy                           0.95       230
   macro avg       0.81      0.97      0.87       230
weighted avg       0.97      0.95      0.95       230
```

Compare the models

In [105]:
```
models = [knn, log_reg, decision_tree, random_forest,svm_model ,naive_b
model_names = ['KNN', 'Logistic Regression', 'Decision Tree', 'Random F
for model, name in zip(models, model_names):
 # Train the model on the training set
 model.fit(X_train, y_train)

 # Validate the model on the validation set
 y_pred_val = model.predict(X_val)

 # Evaluate model performance on validation set
 accuracy_val = accuracy_score(y_val, y_pred_val)
 # Print or store the validation results for comparison
 print(f"{name} Validation Accuracy: {accuracy_val}")
```

```
KNN Validation Accuracy: 0.9902200488997555
Logistic Regression Validation Accuracy: 0.9926650366748166
Decision Tree Validation Accuracy: 1.0
Random Forest Validation Accuracy: 1.0
SVM Validation Accuracy: 1.0
Naive Bayes Validation Accuracy: 0.8936430317848411
```

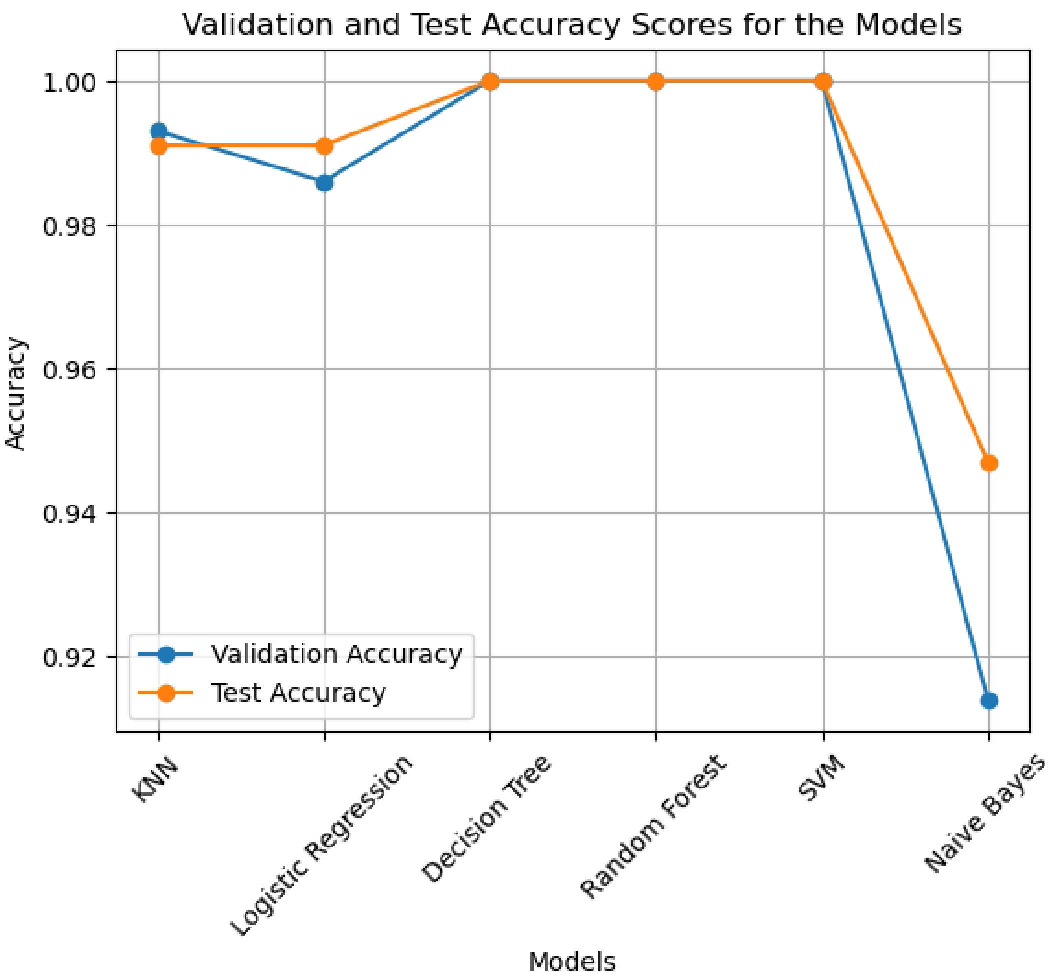
Validation Accuracy Score vs Test Accuracy Score

In [106]:

```
# Validation and test accuracy scores for different models
models = ['KNN', 'Logistic Regression', 'Decision Tree', 'Random Forest
val_scores = [0.990, 0.992, 1.0, 1.0, 1.0, 0.893]
test_scores = [0.991, 0.991, 1.0, 1.0, 1.0, 0.947]

# Create a DataFrame to compare accuracy scores
accuracy_df = pd.DataFrame({'Model': models, 'Validation Accuracy': val_

# Display the comparison table
print(accuracy_df)
```

```
                 Model  Validation Accuracy  Test Accuracy
0                  KNN                0.990          0.991
1  Logistic Regression                0.992          0.991
2        Decision Tree                1.000          1.000
3        Random Forest                1.000          1.000
4                  SVM                1.000          1.000
5          Naive Bayes                0.893          0.947
```

In [107]:
```
#plot line graph
models = ['KNN', 'Logistic Regression', 'Decision Tree', 'Random Forest
val_scores = [0.993, 0.986, 1.0, 1.0, 1.0, 0.914]
test_scores = [0.991, 0.991, 1.0, 1.0, 1.0, 0.947]

plt.plot(models, val_scores, marker='o', label='Validation Accuracy')
plt.plot(models, test_scores, marker='o', label='Test Accuracy')
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.title('Validation and Test Accuracy Scores for the Models')
plt.legend()
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



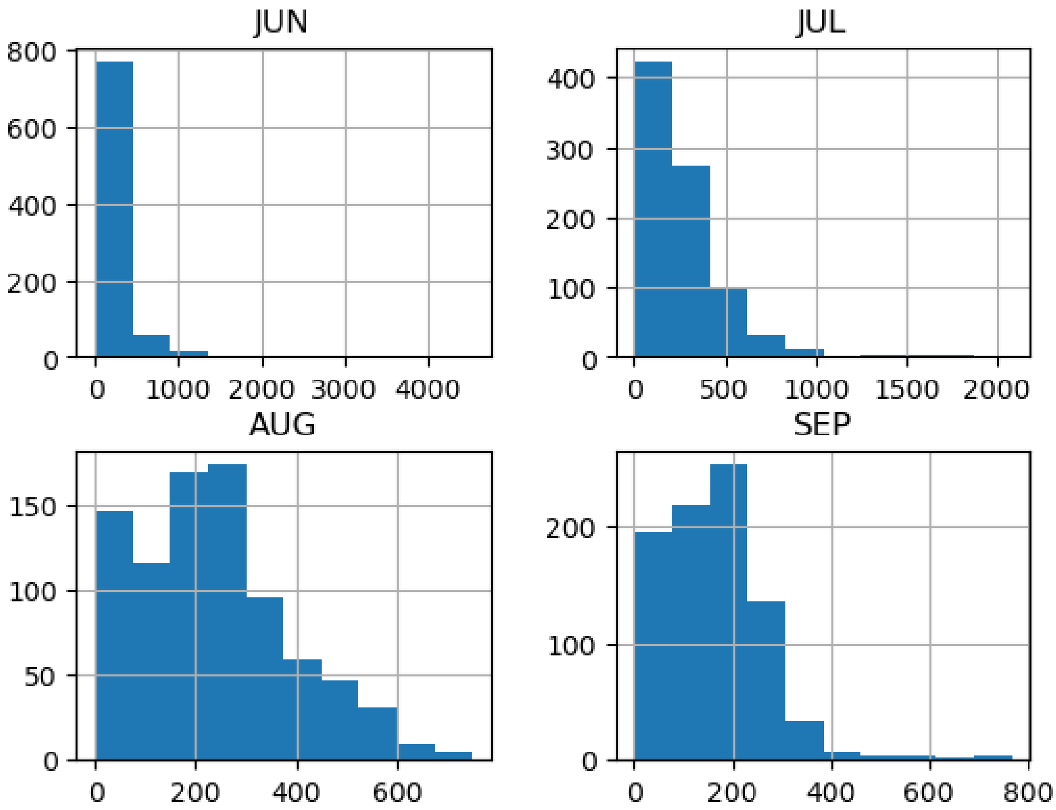
From above, we can observe that Decision Tree, Random Forest and SVM show good accuracy than other models. Let us test the models with an unknown dataset.

Validating with unknown dataset

We used 2022 year rainfall dataset for testing our trained models

In [131]:
```
new_data= pd.read_csv('2022rainfall.csv')
```

In [181]:
```
#Explore how rainfall index varies during rainy season for this unknown
%matplotlib inline
c = new_data[['JUN','JUL','AUG','SEP']]
c.hist()
plt.show()
```



In [132]:
```
new_data.head()
```

Out[132]:

	SUBDIVISIONS	YEAR	JAN	FEB	MAR	APR	MAY	J
0	24 Paraganas North	2022	13.301102	36.471586	3.000000	4.000018	174.932867	103.620
1	24 Paraganas South	2022	17.610375	54.238550	4.536690	4.114744	198.517656	122.403
2	Adilabad	2022	49.152147	2.075905	3.223715	5.998382	27.967830	188.039
3	Agar Malwa	2022	20.066857	2.000000	3.435977	4.000000	5.504517	110.842
4	Agra	2022	27.187090	5.160622	3.000000	4.000000	17.863035	40.238

In [145]:
```
#encoding string to integer
subdiv_encoder = LabelEncoder()
new_data['subdivision_encoded'] = subdiv_encoder.fit_transform(new_data
```

In [150]:

```
#moving the encoded subdivision column infront to easily separate targe
column_order = ['subdivision_encoded', 'SUBDIVISIONS', 'YEAR', 'JAN', '
# Rearrange columns based on 'column_order'
new_data = new_data[column_order]
new_data.head()
```

Out[150]:

	subdivision_encoded	SUBDIVISIONS	YEAR	JAN	FEB	MAR	APR
0	0	24 Paraganas North	2022	13.301102	36.471586	3.000000	4.00001
1	1	24 Paraganas South	2022	17.610375	54.238550	4.536690	4.11474
2	2	Adilabad	2022	49.152147	2.075905	3.223715	5.99838
3	3	Agar Malwa	2022	20.066857	2.000000	3.435977	4.00000
4	4	Agra	2022	27.187090	5.160622	3.000000	4.00000

In [169]:

```
#The data is required in numbers, therefore replace the yes/no in floods
new_data['FLOOD'].replace(['YES','NO'],[1,0],inplace=True)
new_data.head()
```

Out[169]:

JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG
.301102	36.471586	3.000000	4.000018	174.932867	103.620638	161.875981	251.057881
.610375	54.238550	4.536690	4.114744	198.517656	122.403861	153.699521	363.866108
.152147	2.075905	3.223715	5.998382	27.967830	188.039380	962.068860	388.144703
.066857	2.000000	3.435977	4.000000	5.504517	110.842801	496.906508	632.753333
.187090	5.160622	3.000000	4.000000	17.863035	40.238522	240.372088	171.096539

In [170]:

```
testing = new_data.drop('FLOOD', axis=1)
checkvar = new_data['FLOOD']
```

In [171]:

```
testing = testing.drop('SUBDIVISIONS', axis=1)
testing.head()
```

Out[171]:

	subdivision_encoded	YEAR	JAN	FEB	MAR	APR	MAY
0	0	2022	13.301102	36.471586	3.000000	4.000018	174.932867
1	1	2022	17.610375	54.238550	4.536690	4.114744	198.517656
2	2	2022	49.152147	2.075905	3.223715	5.998382	27.967830
3	3	2022	20.066857	2.000000	3.435977	4.000000	5.504517
4	4	2022	27.187090	5.160622	3.000000	4.000000	17.863035

With Decision Tree Model

In [172]:

```
validity_dec_tree = decision_tree.predict(testing)
print(validity_dec_tree)
```

```
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```

In [175]:
```python
# Evaluate performance
accuracy_testing = accuracy_score(checkvar, validity_dec_tree)
print("Validation Accuracy:", accuracy_testing)
```

```
Validation Accuracy: 1.0
```

With SVM model

In [174]:
```python
testing_svm = svm_model.predict(testing)
print(testing_svm)
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
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0 0
 0 0 0]
```

In [176]:
```
# Evaluate performance
accuracy_svm = accuracy_score(checkvar, testing_svm)
print("Validation Accuracy:", accuracy_svm)
```

```
Validation Accuracy: 0.9976580796252927
```

Based on the accuracy scores obtained from testing the 2022 rainfall dataset, it's evident that the Decision Tree model outperforms the SVM model. The accuracy scores showcase that the Decision Tree model exhibits better accuracy when predicting the 2022 rainfall, indicating its superior performance over the SVM model in this specific context.

In [ ]:
```

```