Experiment No. 4
Apply Random Forest Algorithm on Adult Census Income Dataset and analyze the performance of the model
Date of Performance:
Date of Submission:

Aim: Apply Random Forest Algorithm on Adult Census Income Dataset and analyze the performance of the model.

Objective: Able to perform various feature engineering tasks, apply Random Forest Algorithm on the given dataset and maximize the accuracy, Precision, Recall, F1 score.

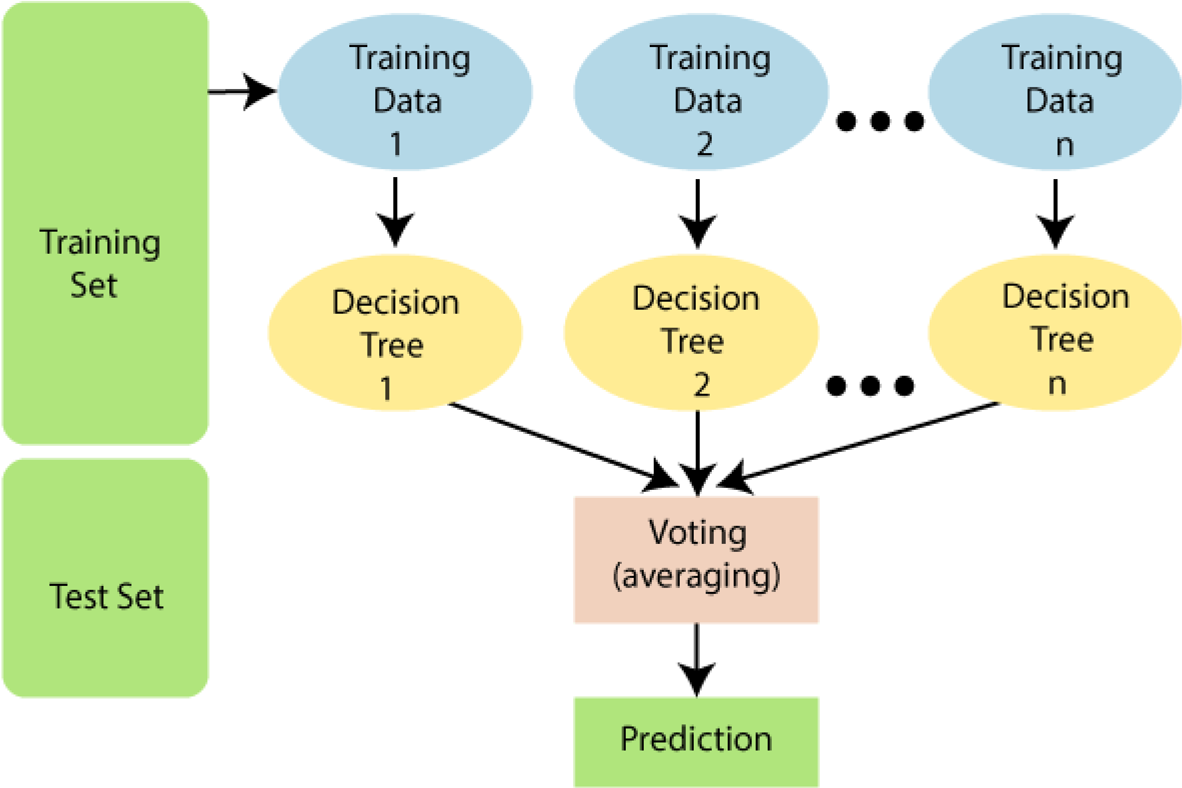
Theory:

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model.

As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

The below diagram explains the working of the Random Forest algorithm:



Dataset:

Predict whether income exceeds $50K/yr based on census data. Also known as "Adult" dataset.

Attribute Information:

Listing of attributes:

>50K, <=50K.

age: continuous.

workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.

fnlwgt: continuous.

education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.

education-num: continuous.

marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.

occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.

relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.

race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.

sex: Female, Male.

capital-gain: continuous.

capital-loss: continuous.

hours-per-week: continuous.

native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad &Tobago, Peru, Hong, Holand-Netherlands.

Code:

Importing lib

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

Load the dataset

```
df = pd.read_csv('adult.csv')
df.head(10)
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	
0	90	?	77053	HS-grad	9	Widowed	?	Not-in-family	White	Fe
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family	White	Fe
2	66	?	186061	Some-college	10	Widowed	?	Unmarried	Black	Fe
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unmarried	White	Fe
4	41	Private	264663	Some-college	10	Separated	Prof-specialty	Own-child	White	Fe
5	34	Private	216864	HS-grad	9	Divorced	Other-service	Unmarried	White	Fe
6	38	Private	150601	10th	6	Separated	Adm-clerical	Unmarried	White	

Understanding Dataset

```
print ("Total Rows     : " ,df.shape[0])
dataset_row = df.shape[0]
print ("Total Columns  : " ,df.shape[1])
print ("\nFeatures : \n" ,df.columns.tolist())
print ("\nMissing values :  ", df.isnull().sum().values.sum())
print ("\nUnique values :  \n",df.nunique())
```

```
Total Rows     :  32561
Total Columns  :  15

Features :
 ['age', 'workclass', 'fnlwgt', 'education', 'education.num', 'marital.status', 'occupation', 'relationship', 'race', 'sex', 'capital.ga

Missing values :   0

Unique values :
 age                  73
workclass             9
fnlwgt            21648
education            16
education.num        16
marital.status        7
occupation           15
relationship          6
race                  5
sex                   2
capital.gain        119
capital.loss         92
hours.per.week       94
native.country       42
income                2
dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
```

```
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             32561 non-null  int64
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64
 3   education       32561 non-null  object
 4   education.num   32561 non-null  int64
 5   marital.status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital.gain    32561 non-null  int64
 11  capital.loss    32561 non-null  int64
 12  hours.per.week  32561 non-null  int64
 13  native.country  32561 non-null  object
 14  income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

```
df.describe()
```

	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	32561.000000
mean	38.581647	1.897784e+05	10.080679	1077.648844	87.303830	40.437456
std	13.640433	1.055500e+05	2.572720	7385.292085	402.960219	12.347429
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.000000
25%	28.000000	1.178270e+05	9.000000	0.000000	0.000000	40.000000
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	40.000000
75%	48.000000	2.370510e+05	12.000000	0.000000	0.000000	45.000000
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	99.000000

Missing Values

```
df_missing = (df=='?').sum()
print(df_missing)
```

```
age                  0
workclass         1836
fnlwgt               0
education            0
education.num        0
marital.status       0
occupation        1843
relationship         0
race                 0
sex                  0
capital.gain         0
capital.loss         0
hours.per.week       0
native.country     583
income               0
dtype: int64
```

percent_missing = (df=='?').sum() * 100/len(df) percent_missing

```
#droping row having missing values from dataset
df = df[df['workclass'] !='?']
df = df[df['occupation'] !='?']
df = df[df['native.country'] !='?']
df.head()
```

age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race

```
df_missing = (df=='?').sum()
print(df_missing)
```

```
age               0
workclass         0
fnlwgt            0
education         0
education.num     0
marital.status    0
occupation        0
relationship      0
race              0
sex               0
capital.gain      0
capital.loss      0
hours.per.week    0
native.country    0
income            0
dtype: int64
```

```
print ("Total Rows after droping rows : " ,df.shape[0])
print("Numbers of rows drop: ", dataset_row -df.shape[0])
```

```
Total Rows after droping rows :  30162
Numbers of rows drop:  2399
```

Data Preparation

```
from sklearn import preprocessing
```

```
df_categorical = df.select_dtypes(include=['object'])
df_categorical.head()
```

	workclass	education	marital.status	occupation	relationship	race	sex	native.country	income
1	Private	HS-grad	Widowed	Exec-managerial	Not-in-family	White	Female	United-States	<=50K
3	Private	7th-8th	Divorced	Machine-op-inspct	Unmarried	White	Female	United-States	<=50K
4	Private	Some-college	Separated	Prof-specialty	Own-child	White	Female	United-States	<=50K
				Other-					

```
le = preprocessing.LabelEncoder()
df_categorical = df_categorical.apply(le.fit_transform)
df_categorical.head()
```

	workclass	education	marital.status	occupation	relationship	race	sex	native.country	income
1	2	11	6	3	1	4	0	38	0
3	2	5	0	6	4	4	0	38	0
4	2	15	5	9	3	4	0	38	0
5	2	11	0	7	4	4	0	38	0
6	2	0	5	0	4	4	1	38	0

```
df = df.drop(df_categorical.columns,axis=1)
df = pd.concat([df,df_categorical],axis=1)
df['income'] = df['income'].astype('category')
df.head()
```

	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week	workclass	education	marita
1	82	132870	9	0	4356	18	2	11	
3	54	140359	4	0	3900	40	2	5	
4	41	264663	10	0	3900	40	2	15	

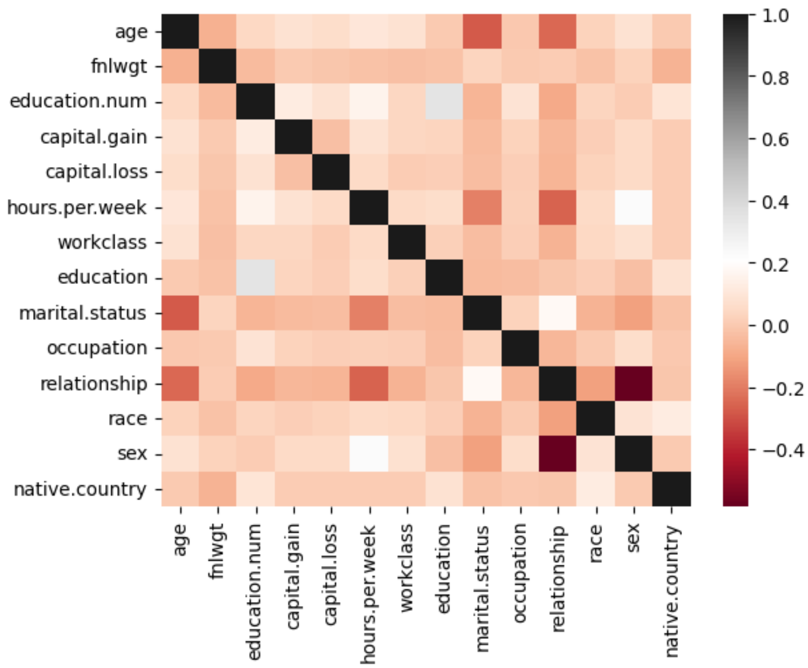
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30162 entries, 1 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             30162 non-null  int64
 1   fnlwgt          30162 non-null  int64
 2   education.num   30162 non-null  int64
 3   capital.gain    30162 non-null  int64
 4   capital.loss    30162 non-null  int64
 5   hours.per.week  30162 non-null  int64
 6   workclass       30162 non-null  int64
 7   education       30162 non-null  int64
 8   marital.status  30162 non-null  int64
 9   occupation      30162 non-null  int64
 10  relationship    30162 non-null  int64
 11  race            30162 non-null  int64
 12  sex             30162 non-null  int64
 13  native.country  30162 non-null  int64
 14  income          30162 non-null  category
dtypes: category(1), int64(14)
memory usage: 3.5 MB
```

Visualization

```
sns.heatmap(df.corr(), cmap = 'RdGy')
```

```
<ipython-input-249-b22fcbbd6ef9>:1: FutureWarning: The default value of numeric_only in DataFrame.corr
  sns.heatmap(df.corr(), cmap = 'RdGy')
<Axes: >
```



Spliting dataset

```
from sklearn.model_selection import train_test_split
```

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

```
X.head()
```

	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week	workclass	education	marita
1	82	132870	9	0	4356	18	2	11	
3	54	140359	4	0	3900	40	2	5	
4	41	264663	10	0	3900	40	2	15	
5	34	216864	9	0	3770	45	2	11	
6	38	150601	6	0	3770	40	2	0	

```
y.head()
```

```
1    0
3    0
4    0
5    0
6    0
Name: income, dtype: category
Categories (2, int64): [0, 1]
```

```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.20)
```

Appling RandomForest Algo

```
from sklearn.ensemble import RandomForestClassifier
```

```
dt_default = RandomForestClassifier(max_depth=5)
dt_default.fit(X_train,y_train)
```

```
▾      RandomForestClassifier
RandomForestClassifier(max_depth=5)
```

```
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
```

```
y_pred_default = dt_default.predict(X_test)
print("confusion matrix\n",confusion_matrix(y_test,y_pred_default))
print(classification_report(y_test,y_pred_default))
```

```
confusion matrix
 [[4298  165]
 [ 769  801]]
              precision    recall  f1-score   support

           0       0.85      0.96      0.90      4463
           1       0.83      0.51      0.63      1570

    accuracy                           0.85      6033
   macro avg       0.84      0.74      0.77      6033
weighted avg       0.84      0.85      0.83      6033
```

```
print("accuracy score: ",accuracy_score(y_test,y_pred_default))
```

```
accuracy score:  0.8451848168407095
```

Conclusion:

1. **Observations from the Correlation Heat Map:**

The correlation heat map is a useful tool for understanding the relationships between different features in the dataset. In the correlation heatmap, we can observe that the "relationship" and "sex" features exhibit a correlation. Consequently, it suggests that one of these features could be removed to potentially reduce multi-collinearity

2. **Performance Metrics:**

Accuracy gauges overall correctness, the confusion matrix details true/false predictions, precision focuses on accurate positive classifications, recall identifies relevant instances, and F1-Score balances precision and recall, crucial for imbalanced classes.

```
confusion matrix
 [[4298  165]
 [ 769  801]]
              precision    recall  f1-score   support

           0       0.85      0.96      0.90      4463
           1       0.83      0.51      0.63      1570
    accuracy                           0.85      6033
   macro avg       0.84      0.74      0.77      6033
weighted avg       0.84      0.85      0.83      6033
```

.

3. **Comparison with Decision Tree Algorithm:**

Result obtain using decision tree were:

```
confusion matrix
 [[4310  243]
 [ 713  767]]
              precision    recall  f1-score   support

           0       0.86      0.95      0.90      4553
           1       0.76      0.52      0.62      1480
    accuracy                           0.84      6033
   macro avg       0.81      0.73      0.76      6033
weighted avg       0.83      0.84      0.83      6033
```

Both the Decision Tree and Random Forest models achieved an accuracy of approximately 85%, indicating that they correctly predicted income levels for most individuals. However, they exhibited lower recall for the higher income class (1), indicating a tendency to miss some individuals with incomes over 50K, despite having good precision for the lower income class (0).