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| 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.

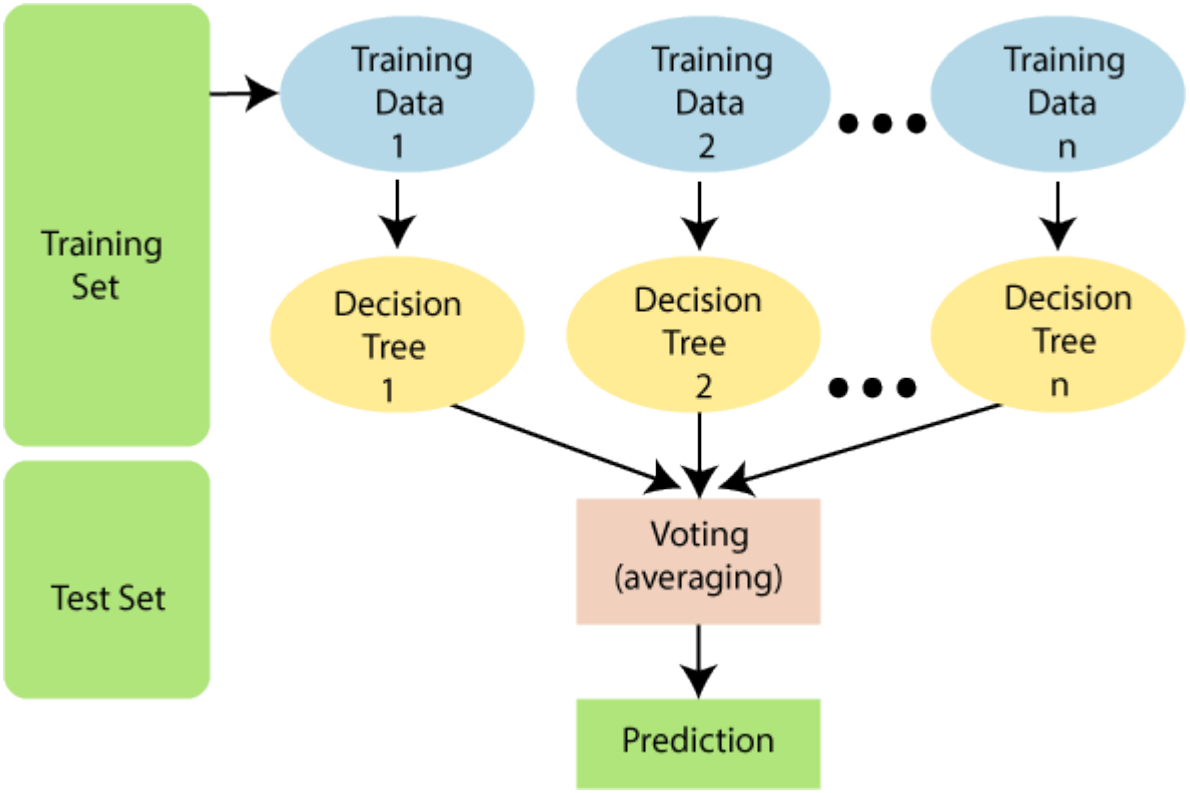
**Theory:**

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:**

**Conclusion:**

1. State the observations about the data set from the correlation heat map.

   Looking at the correlation heatmap, positive correlations suggest that as one feature increases, the other typically increases as well. In this dataset, we observe a positive correlation between "education_num" and "income," implying that higher education levels tend to be associated with higher income. On the other hand, negative correlations indicate that as one feature increases, the other tends to decrease. For instance, there's a negative correlation between "age" and "hours_per_week," suggesting that older employees tend to work fewer hours per week.

2. Comment on the accuracy, confusion matrix, precision, recall and F1 score obtained.

   The model's accuracy stands at approximately 85%, signifying that it correctly predicts the income level (either >50K or <=50K) for 85% of the test dataset. The confusion matrix offers a more detailed analysis. The model correctly predicts 802 cases where income is >50K (True Positives, TP) and 4319 cases where income is <=50K (True Negatives, TN). However, it also makes 181 false positive predictions (False Positives, FP) and 731 false negative predictions (False Negatives, FN). Precision for the income class >50K is roughly 0.68, meaning that when the model predicts a positive outcome (income >50K), it's correct about 87% of the time. The recall for the same class is approximately 0.45, indicating that the model correctly identifies about 45% of all instances where income is indeed greater than 50K. The F1-score for this class is approximately 0.54, showing a reasonable balance between precision and recall in predicting incomes greater than 50K.

3. Compare the results obtained by applying random forest and decision tree algorithm on the Adult Census Income Dataset

   When comparing the results of the Decision Tree and Random Forest algorithms on the Adult Census Income Dataset, we find that both models achieve a similar accuracy of around 85%, correctly predicting income levels for individuals. However, they both exhibit lower recall for the higher income class (class 1), suggesting that they tend to miss some individuals with incomes greater than 50K.

```
!pip install scikit-plot
!pip install -U seaborn
```

```
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split,cross_val_score,KFold,GridSearchCV
from sklearn.metrics import confusion_matrix,classification_report,accuracy_score
import scikitplot as skplt
```

```
dataset=pd.read_csv("/content/adult.csv")
```

```
print(dataset.isnull().sum())
print(dataset.dtypes)
```

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

```
dataset.head()
```

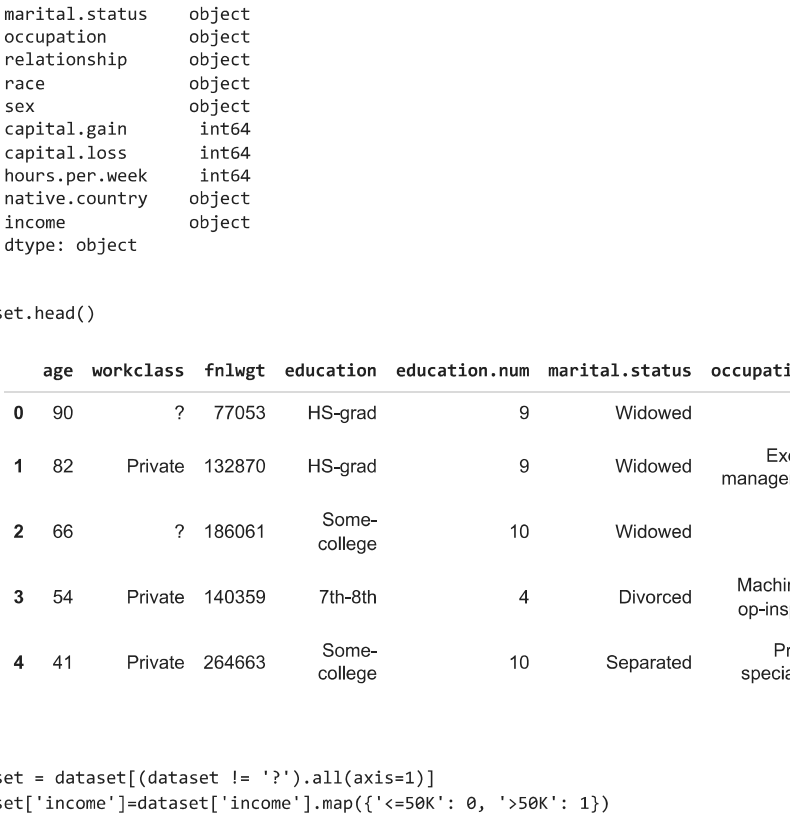
| | age | workclass | fnlwgt | education | education.num | marital.status | occupation | relationship | race | sex | capital.gain | capital.loss | hours.per.week | native.cou |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 90 | ? | 77053 | HS-grad | 9 | Widowed | ? | Not-in-family | White | Female | 0 | 4356 | 40 | United-S |
| **1** | 82 | Private | 132870 | HS-grad | 9 | Widowed | Exec-managerial | Not-in-family | White | Female | 0 | 4356 | 18 | United-S |
| **2** | 66 | ? | 186061 | Some-college | 10 | Widowed | ? | Unmarried | Black | Female | 0 | 4356 | 40 | United-S |
| **3** | 54 | Private | 140359 | 7th-8th | 4 | Divorced | Machine-op-inspct | Unmarried | White | Female | 0 | 3900 | 40 | United-S |
| **4** | 41 | Private | 264663 | Some-college | 10 | Separated | Prof-specialty | Own-child | White | Female | 0 | 3900 | 40 | United-S |

```
dataset = dataset[(dataset != '?').all(axis=1)]
dataset['income']=dataset['income'].map({'<=50K': 0, '>50K': 1})
```

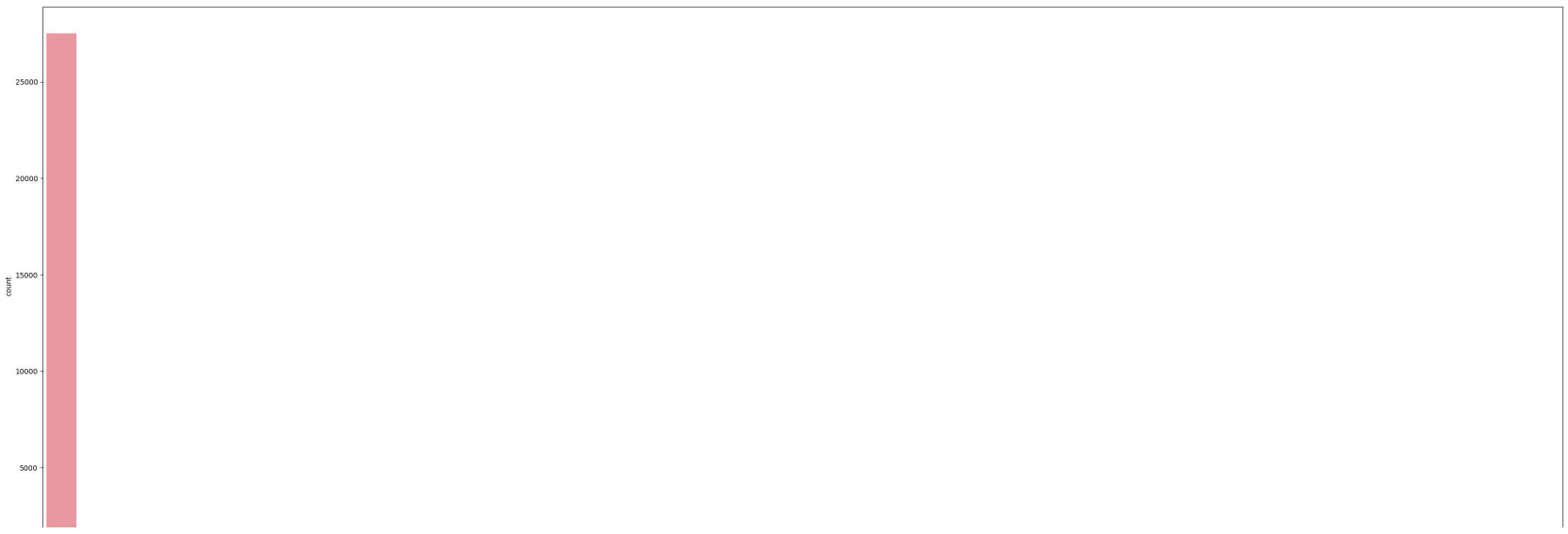
```
<ipython-input-7-39ed73805135>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  dataset['income']=dataset['income'].map({'<=50K': 0, '>50K': 1})
```

```
sns.catplot(x='education.num',y='income',data=dataset,kind='bar',height=6)
plt.show()
```



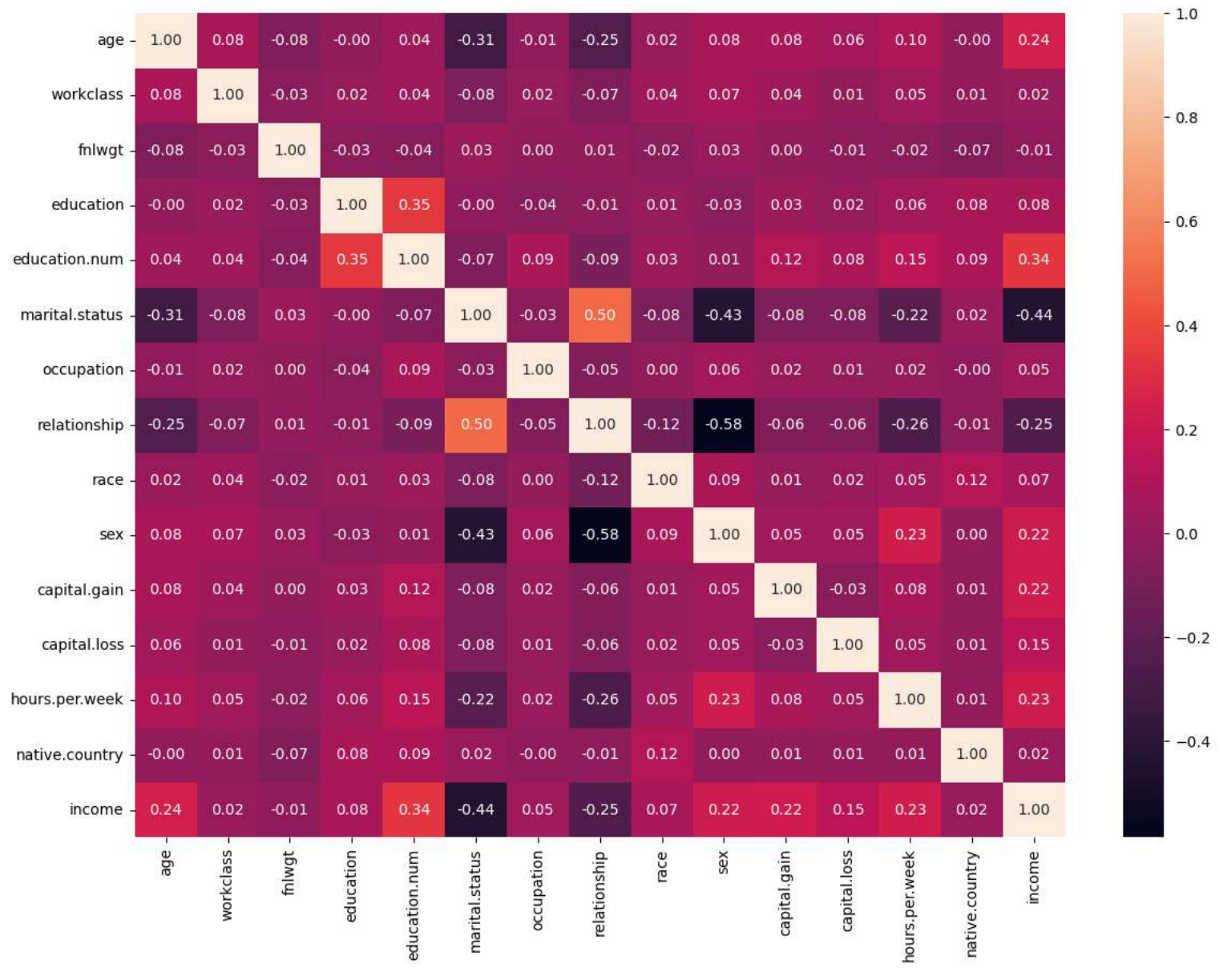

```
plt.figure(figsize=(38,14))
sns.countplot(x='native.country',data=dataset)
plt.show()
```




```
dataset['marital.status']=dataset['marital.status'].map({'Married-civ-spouse':'Married', 'Divorced':'Single', 'Never-married':'Single', 'Separated':'Single',
'Widowed':'Single', 'Married-spouse-absent':'Married', 'Married-AF-spouse':'Married'})


for column in dataset:
    enc=LabelEncoder()
    if dataset.dtypes[column]==np.object:
         dataset[column]=enc.fit_transform(dataset[column])


plt.figure(figsize=(14,10))
sns.heatmap(dataset.corr(),annot=True,fmt='.2f')
plt.show()
```




```
dataset=dataset.drop(['relationship','education'],axis=1)


dataset=dataset.drop(['occupation','fnlwgt','native.country'],axis=1)


print(dataset.head())
```

```
    age  workclass  education.num  marital.status  race  sex  capital.gain  \
1    82          2              9               1     4    0             0
3    54          2              4               1     4    0             0
4    41          2             10               1     4    0             0
5    34          2              9               1     4    0             0
6    38          2              6               1     4    1             0

    capital.loss  hours.per.week  income
1           4356              18       0
3           3900              40       0
4           3900              40       0
5           3770              45       0
6           3770              40       0
```

```
X=dataset.iloc[:,0:-1]
y=dataset.iloc[:,-1]
print(X.head())
print(y.head())
x_train,x_test,y_train,y_test=train_test_split(X,y,test_size=0.33,shuffle=False)
```

```
    age  workclass  education.num  marital.status  race  sex  capital.gain  \
1    82          2              9               1     4    0             0
3    54          2              4               1     4    0             0
4    41          2             10               1     4    0             0
5    34          2              9               1     4    0             0
6    38          2              6               1     4    1             0

    capital.loss  hours.per.week
1           4356              18
3           3900              40
4           3900              40
5           3770              45
6           3770              40
1    0
3    0
4    0
5    0
```

```
6    0
Name: income, dtype: int64
```

```
clf=GaussianNB()
cv_res=cross_val_score(clf,x_train,y_train,cv=10)
print(cv_res.mean()*100)
```

```
76.68213951528749
```

```
clf=DecisionTreeClassifier()
cv_res=cross_val_score(clf,x_train,y_train,cv=10)
print(cv_res.mean()*100)
```

```
74.22335771429692
```

```
clf=RandomForestClassifier(n_estimators=100)
cv_res=cross_val_score(clf,x_train,y_train,cv=10)
print(cv_res.mean()*100)
```

```
76.75196574580762
```

```
clf=RandomForestClassifier(n_estimators=50,max_features=5,min_samples_leaf=50)
clf.fit(x_train,y_train)
```

RandomForestClassifier

```
RandomForestClassifier(max_features=5, min_samples_leaf=50, n_estimators=50)
```

```
pred=clf.predict(x_test)
pred
```

```
array([1, 1, 1, ..., 0, 0, 0])
```

```
print("Accuracy: %f " % (100*accuracy_score(y_test, pred)))
print(confusion_matrix(y_test,pred))
print(classification_report(y_test,pred))
```

```
Accuracy: 84.639341
[[7515  427]
 [1102  910]]
              precision    recall  f1-score   support

           0       0.87      0.95      0.91      7942
           1       0.68      0.45      0.54      2012

    accuracy                           0.85      9954
   macro avg       0.78      0.70      0.73      9954
weighted avg       0.83      0.85      0.83      9954
```