DATA PREPROCESSING AND LOADING

1. LOGISTIC REGRESSION

```
# Import necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix


# Generate some sample data
np.random.seed(0)
data = {
    'Exam1': np.random.rand(100) * 100,
    'Exam2': np.random.rand(100) * 100,
    'Admitted': np.random.randint(2, size=100)
}
df = pd.DataFrame(data)
print(df)
#
# # Split the data into features (X) and target (y)
X = df[['Exam1', 'Exam2']]
y = df['Admitted']
print(X)
print(y)
```

```
#
# # Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
#
# # Create a logistic regression model
model = LogisticRegression()
#
# # Fit the model to the training data
model.fit(X_train, y_train)
#
# # Make predictions on the test data
y_pred = model.predict(X_test)
print("------------------")
print(y_pred)
#
# # Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')
#
# # Display classification report and confusion matrix
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
#
# Plot the decision boundary
# x_min, x_max = X['Exam1'].min() - 10, X['Exam1'].max() + 10
```

```
# y_min, y_max = X['Exam2'].min() - 10, X['Exam2'].max() + 10

# xx, yy = np.meshgrid(np.linspace(x_min, x_max, 100), np.linspace(y_min, y_max, 100))

# Z = model.predict(np.c_[xx.ravel(), yy.ravel()])

# Z = Z.reshape(xx.shape)

#

# plt.contourf(xx, yy, Z, cmap=plt.cm.RdBu, alpha=0.8)

# plt.scatter(X['Exam1'], X['Exam2'], c=y, cmap=plt.cm.RdBu)

# plt.xlabel('Exam 1 Score')

# plt.ylabel('Exam 2 Score')

# plt.title('Logistic Regression Decision Boundary')

# plt.show()
```

Output:

```
         Exam1       Exam2  Admitted
0   54.881350  67.781654         0
1   71.518937  27.000797         1
2   60.276338  73.519402         0
3   54.488318  96.218855         0
4   42.365480  24.875314         1
..        ...        ...       ...
95  18.319136  49.045881         0
96  58.651293  22.741463         1
97   2.010755  25.435648         0
98  82.894003   5.802916         1
99   0.469548  43.441663         0

[100 rows x 3 columns]
         Exam1       Exam2
0   54.881350  67.781654
1   71.518937  27.000797
2   60.276338  73.519402
3   54.488318  96.218855
4   42.365480  24.875314
..        ...        ...
95  18.319136  49.045881
96  58.651293  22.741463
97   2.010755  25.435648
```

2. CONFUSION MATRIX

```
#scikit-learn
from sklearn.datasets import make_classification

value1, y = make_classification(
    n_features=6,
    n_classes=2,
    n_samples=800,
    n_informative=2,
    random_state=66,
    n_clusters_per_class=1,
)
```

##. This code imports the make_classification function from the sklearn.datasets module.

##• The make_classification function generates a random dataset for classification tasks.

##• The function takes several arguments: n_features: the number of features (or independent variables) in the dataset.

##• In this case, there are 6 features.

##• n_classes: the number of classes (or target variables) in the dataset.

##• In this case, there are 3 classes.

##• n_samples: the number of samples (or observations) in the dataset.

##• In this case, there are 800 samples.

##• n_informative: the number of informative features in the dataset.

##• These are the features that actually influence the target variable.

##• In this case, there are 2 informative features.

##• random_state: a seed value for the random number generator.

##• This ensures that the dataset is reproducible.

##• n_clusters_per_class: the number of clusters per class.

##• This determines the degree of separation between the classes.

##• In this case, there is only 1 cluster per class.

##• The function returns two arrays: X: an array of shape (n_samples, n_features) containing the features of the dataset.

##• y: an array of shape (n_samples,) containing the target variable of the dataset.

```
import matplotlib.pyplot as plt


plt.scatter(value1[:, 0], value1[:, 1], c=y, marker="*")

plt.show()
```

##This code imports the matplotlib.pyplot module and creates a scatter plot using the scatter() function.

##• The X and y variables are assumed to be previously defined arrays or data frames.

##• The scatter() function takes three arguments: X[:, 0] and X[:, 1] are the first and second columns of the X array, respectively, and c=y assigns a color to each point based on the corresponding value in the y array.

##• The marker argument specifies the shape of the marker used for each point, in this case, an asterisk.

##• The resulting plot will have the values in the first column of X on the x-axis, the values in the second column of X on the y-axis, and each point will be colored based on the corresponding value in y.

```
from sklearn.model_selection import train_test_split


X_train, X_test, y_train, y_test = train_test_split(

   value1, y, test_size=0.33, random_state=125

)
```

##This code imports the train_test_split function from the sklearn.model_selection module.

##• This function is used to split the dataset into training and testing sets.

##• The train_test_split function takes four arguments: X, y, test_size, and random_state.

##• X and y are the input features and target variable, respectively.

##• test_size is the proportion of the dataset that should be allocated to the testing set.

##• In this case, it is set to 0.33, which means that 33% of the data will be used for testing.

##• random_state is used to set the seed for the random number generator, which ensures that the same random split is generated each time the code is run.

##• The function returns four variables: X_train, X_test, y_train, and y_test.

##• X_train and y_train are the training set, while X_test and y_test are the testing set.

##• These variables can be used to train and evaluate a machine learning model.

```
from sklearn.naive_bayes import GaussianNB

# Build a Gaussian Classifier
model = GaussianNB()

# Model training
model.fit(X_train, y_train)

# Predict Output
predicted = model.predict([X_test[6]])
#
print("Actual Value:", y_test[6])
print("Predicted Value:", predicted[0])
```

##This code uses the scikit-learn library to build a Gaussian Naive Bayes classifier.

##• First, the code imports the GaussianNB class from the sklearn.naive_bayes module.

##• Next, a new instance of the GaussianNB class is created and assigned to the variable 'model'.

##• The model is then trained using the fit() method, which takes in the training data X_train and the corresponding target values y_train.

##• After the model is trained, it is used to predict the output for a single test data point, which is the 7th element in the X_test array.

##• The predicted value is stored in the 'predicted' variable.

##• Finally, the actual value for the test data point is printed using y_test[6], and the predicted value is printed using predicted[0].

#----------

```
from sklearn.metrics import (
   accuracy_score,
   confusion_matrix,
   ConfusionMatrixDisplay,
   f1_score,
)

y_pred = model.predict(X_test)
accuray = accuracy_score(y_pred, y_test)
f1 = f1_score(y_pred, y_test, average="weighted")

print("Accuracy:", accuray)
print("F1 Score:", f1)
```

##This code imports several functions from the sklearn.metrics module, including accuracy_score, confusion_matrix, ConfusionMatrixDisplay, and f1_score.

##• These functions are used to evaluate the performance of a machine learning model.

##• The code then uses the model.predict method to generate predictions for the test data (X_test).

##• These predictions are compared to the actual labels (y_test) using the accuracy_score and f1_score functions.

##• The accuracy_score function calculates the accuracy of the model's predictions,

while the f1_score function calculates the F1 score, which is a weighted average of precision and recall.

##• Finally, the code prints out the accuracy and F1 score of the model's predictions.

#----------

#####Expected output

####

####Accuracy: 0.8484848484848485

####F1 Score: 0.8491119695890328

####This code snippet is not actually a code, but rather the output of some code that was run.

####• It shows the accuracy and F1 score of a model that was trained on some data.

####• The accuracy is 0.8484848484848485,

which means that the model correctly predicted the outcome of 84.8% of the cases.

####• The F1 score is 0.8491119695890328,

which is a measure of the model's accuracy that takes into account both precision and recall.

####• A higher F1 score indicates better performance of the model.

#----------

```
labels = [0,1,2]
cm = confusion_matrix(y_test, y_pred, labels=labels)
print(cm)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=labels)
disp.plot()
```

########This code is using the scikit-learn library to create a confusion matrix and display it using ConfusionMatrixDisplay.

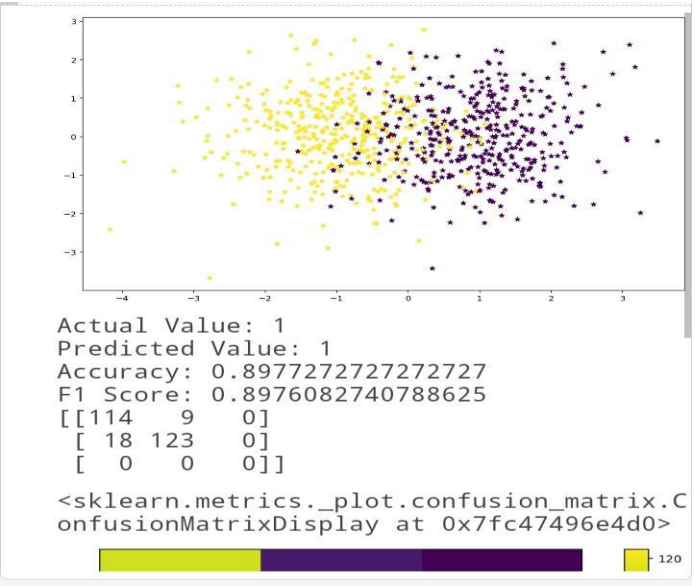
########• First, a list of labels is created with the values 0, 1, and 2.

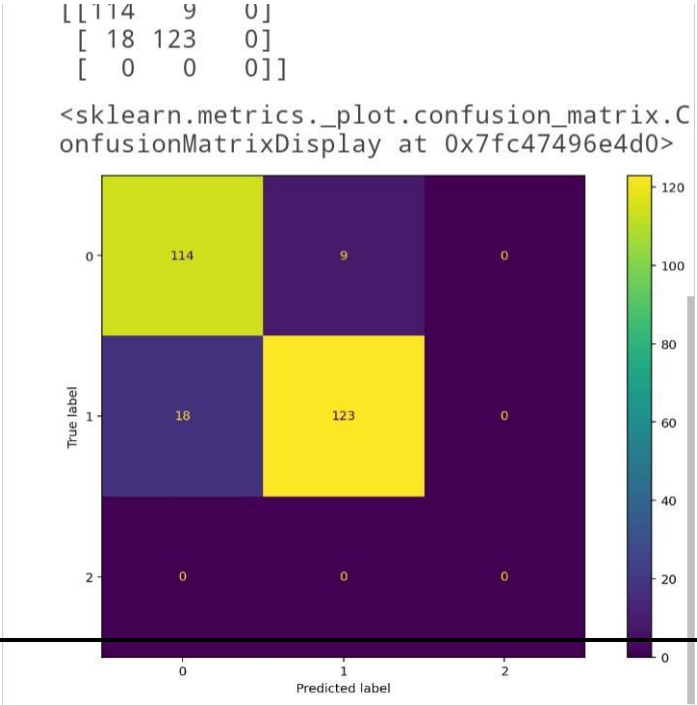
########• Then, the confusion_matrix function is called with the test labels (y_test) and predicted labels (y_pred) as inputs, along with the labels list.

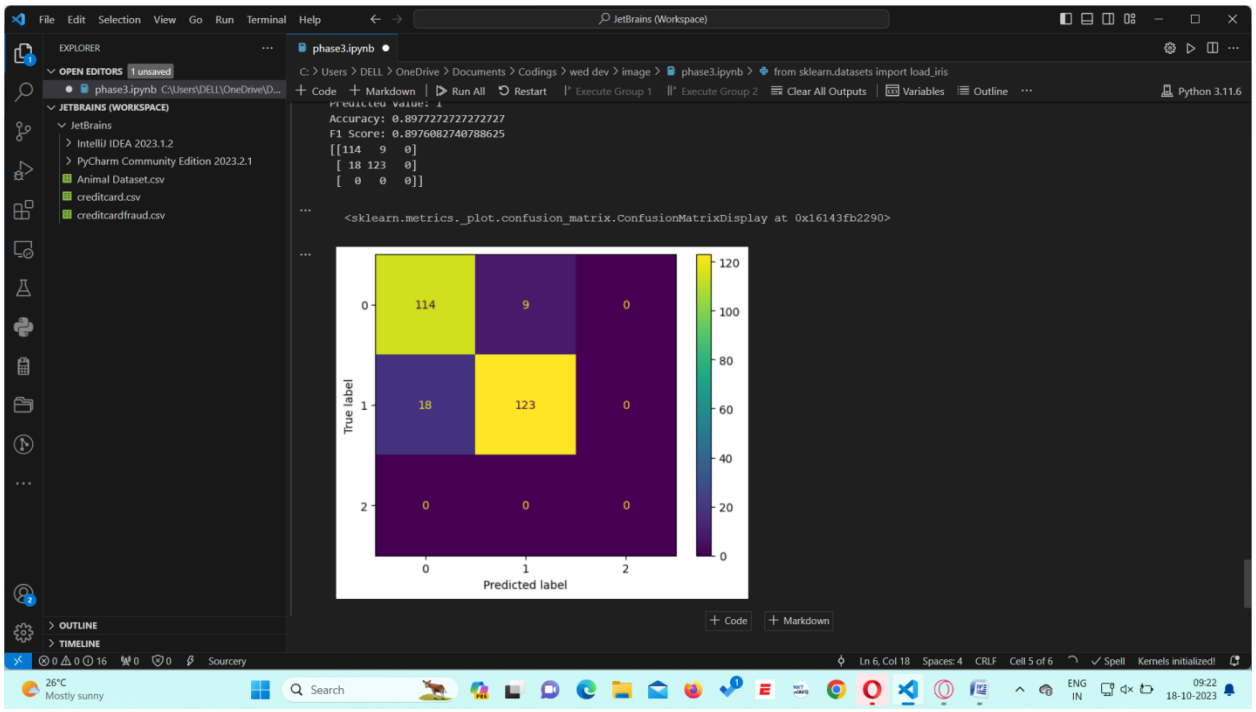
########• This creates a confusion matrix with the specified labels.

########• Next, a ConfusionMatrixDisplay object is created with the confusion matrix as input, along with the labels list.

########• Finally, the plot method is called on the display object to show the confusion matrix graphically.







Run this program on your local python

interpreter, provided you have installed

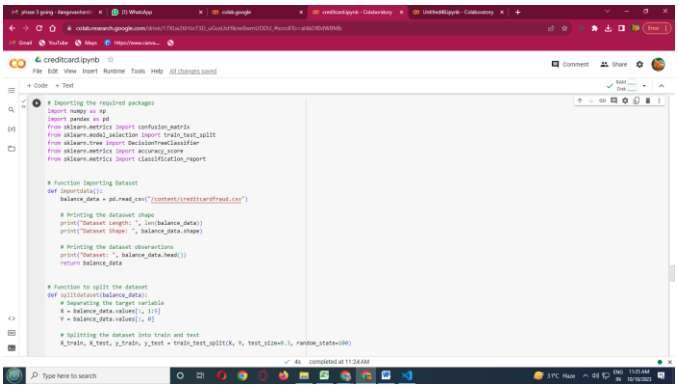
the required libraries.

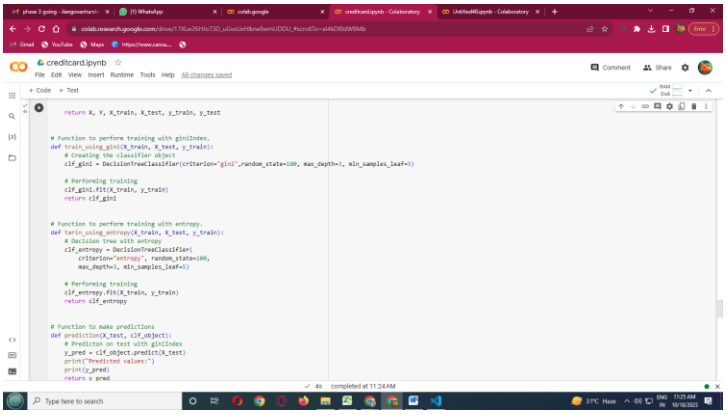
```
# Importing the required packages
import numpy as np
import pandas as pd
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report


# Function importing Dataset
def importdata():
    balance_data = pd.read_csv(
        'https://archive.ics.uci.edu/ml/machine-learning-' +
        'databases/balance-scale/balance-scale.data',
        sep=',', header=None)

    # Printing the dataswet shape
    print("Dataset Length: ", len(balance_data))
    print("Dataset Shape: ", balance_data.shape)

    # Printing the dataset obseravtions
    print("Dataset: ", balance_data.head())
    return balance_data


# Function to split the dataset
def splitdataset(balance_data):
```

```
    # Separating the target variable
    X = balance_data.values[:, 1:5]
    Y = balance_data.values[:, 0]

    # Splitting the dataset into train and test
    X_train, X_test, y_train, y_test = train_test_split(
        X, Y, test_size=0.3, random_state=100)

    return X, Y, X_train, X_test, y_train, y_test


# Function to perform training with giniIndex.
def train_using_gini(X_train, X_test, y_train):
    # Creating the classifier object
    clf_gini = DecisionTreeClassifier(criterion="gini",
                                      random_state=100, max_depth=3, min_samples_leaf=5)

    # Performing training
    clf_gini.fit(X_train, y_train)
    return clf_gini


# Function to perform training with entropy.
def tarin_using_entropy(X_train, X_test, y_train):
    # Decision tree with entropy
    clf_entropy = DecisionTreeClassifier(
        criterion="entropy", random_state=100,
        max_depth=3, min_samples_leaf=5)
```

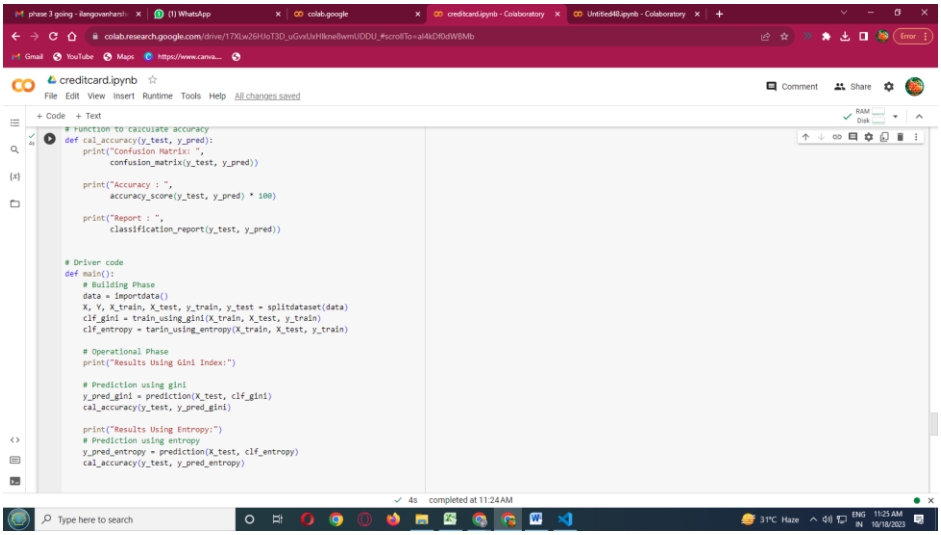
```
    # Performing training
    clf_entropy.fit(X_train, y_train)
    return clf_entropy


# Function to make predictions
def prediction(X_test, clf_object):
    # Predicton on test with giniIndex
    y_pred = clf_object.predict(X_test)
    print("Predicted values:")
    print(y_pred)
    return y_pred


# Function to calculate accuracy
def cal_accuracy(y_test, y_pred):
    print("Confusion Matrix: ",
        confusion_matrix(y_test, y_pred))

    print("Accuracy : ",
        accuracy_score(y_test, y_pred) * 100)

    print("Report : ",
        classification_report(y_test, y_pred))


# Driver code
def main():
    # Building Phase
```

```
    data = importdata()
    X, Y, X_train, X_test, y_train, y_test = splitdataset(data)
    clf_gini = train_using_gini(X_train, X_test, y_train)
    clf_entropy = tarin_using_entropy(X_train, X_test, y_train)

    # Operational Phase
    print("Results Using Gini Index:")

    # Prediction using gini
    y_pred_gini = prediction(X_test, clf_gini)
    cal_accuracy(y_test, y_pred_gini)

    print("Results Using Entropy:")
    # Prediction using entropy
    y_pred_entropy = prediction(X_test, clf_entropy)
    cal_accuracy(y_test, y_pred_entropy)


# Calling main function
if __name__ == "__main__":
    main()
```

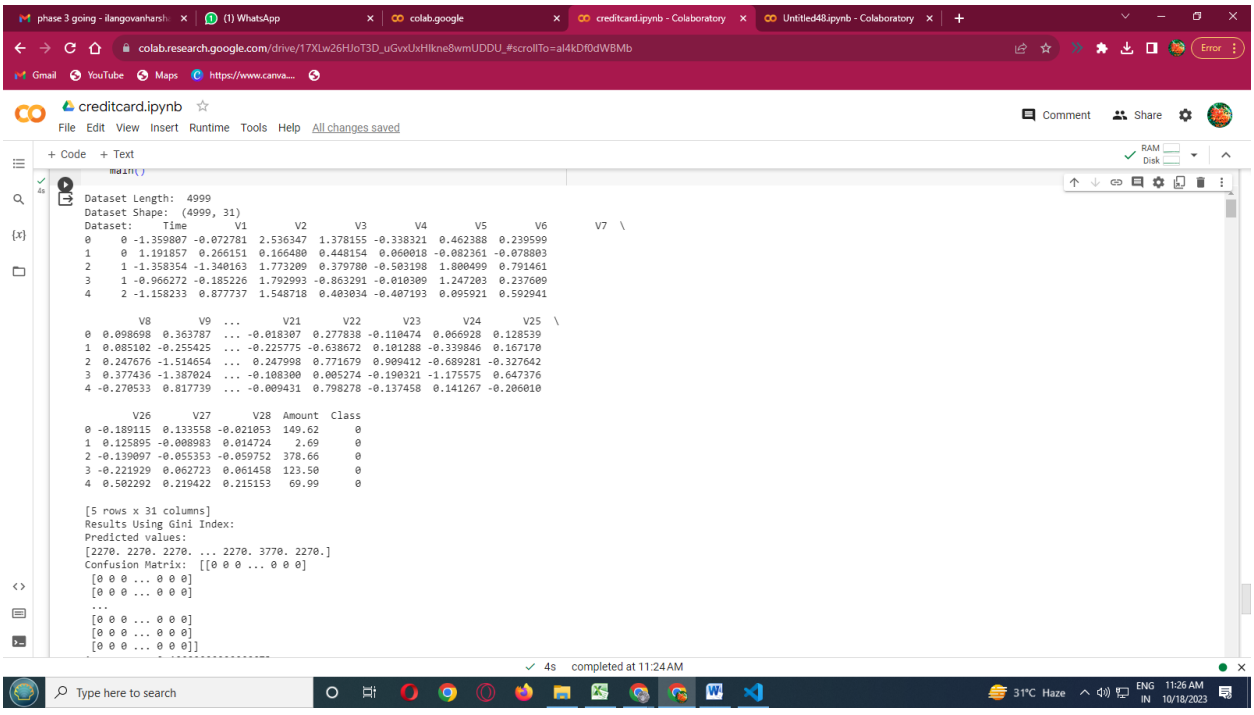




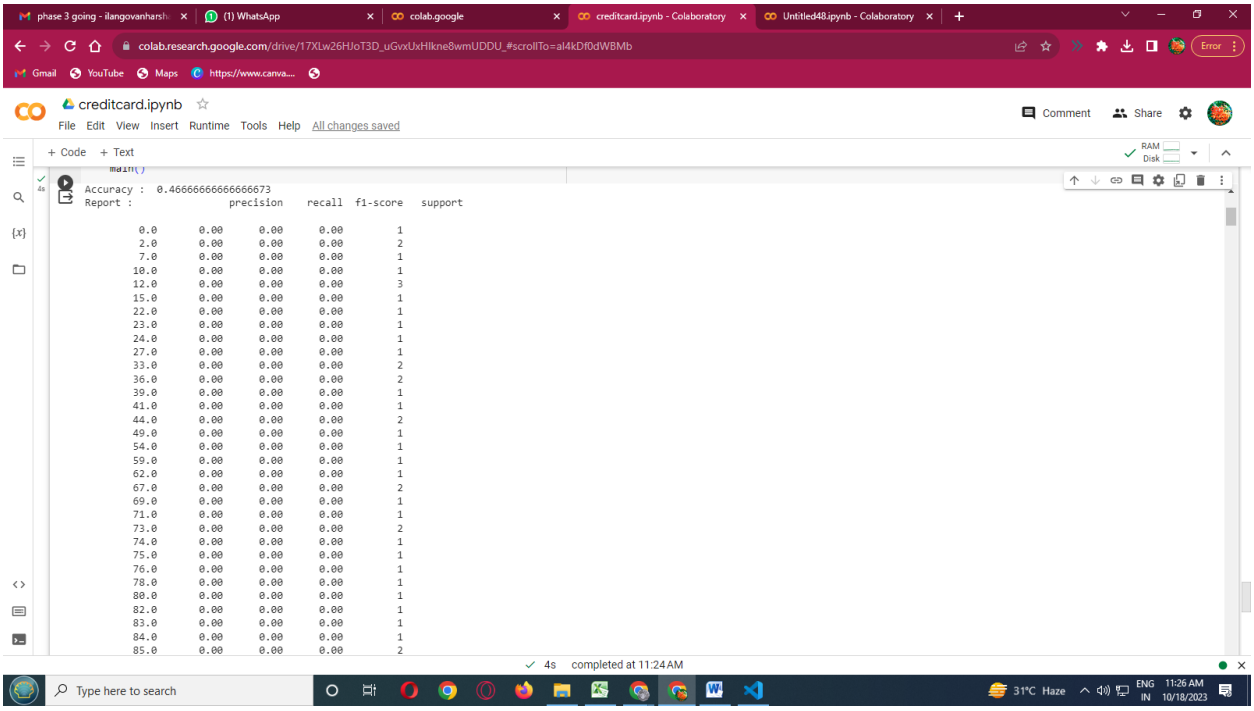
```
    return X, Y, X_train, X_test, y_train, y_test

# Function to perform training with giniIndex.
def train_using_gini(X_train, X_test, y_train):
    # Creating the classifier object
    clf_gini = DecisionTreeClassifier(criterion="gini",random_state=100, max_depth=3, min_samples_leaf=5)

    # Performing training
    clf_gini.fit(X_train, y_train)
    return clf_gini


# Function to perform training with entropy.
def tarin_using_entropy(X_train, X_test, y_train):
    # Decision tree with entropy
    clf_entropy = DecisionTreeClassifier(
        criterion="entropy", random_state=100,
        max_depth=3, min_samples_leaf=5)

    # Performing training
    clf_entropy.fit(X_train, y_train)
    return clf_entropy


# Function to make predictions
def prediction(X_test, clf_object):
    # Predicton on test with giniIndex
    y_pred = clf_object.predict(X_test)
    print("Predicted values:")
    print(y_pred)
    return y_pred
```



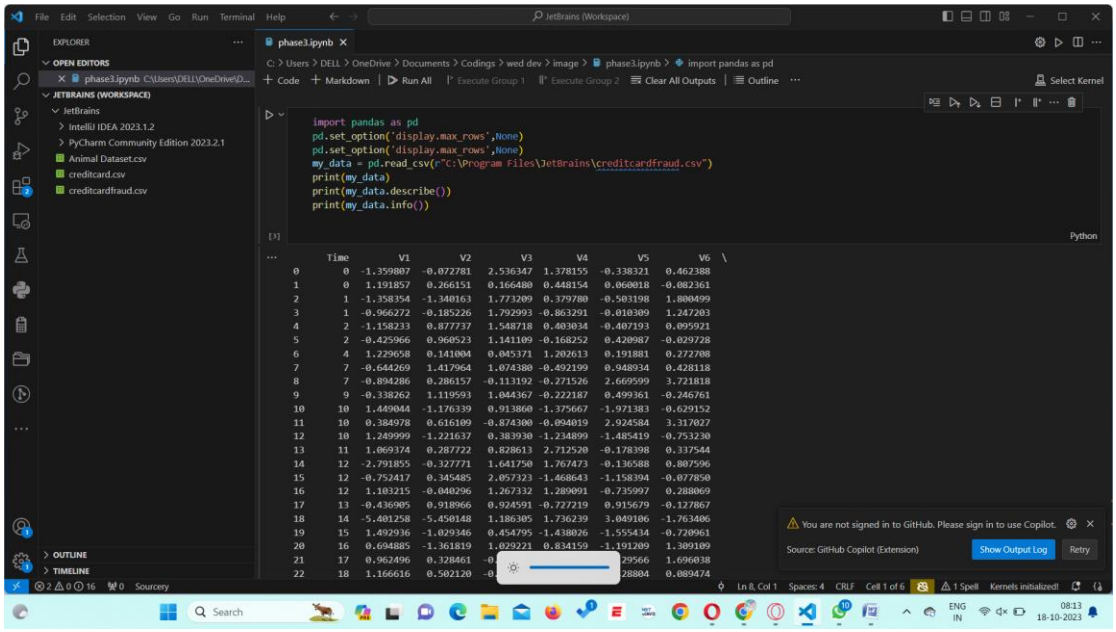
```
# Function to calculate accuracy
def cal_accuracy(y_test, y_pred):
    print("Confusion Matrix: ",
          confusion_matrix(y_test, y_pred))

    print("Accuracy : ",
          accuracy_score(y_test, y_pred) * 100)

    print("Report : ",
          classification_report(y_test, y_pred))


# Driver code
def main():
    # Building Phase
    data = importdata()
    X, Y, X_train, X_test, y_train, y_test = splitdataset(data)
    clf_gini = train_using_gini(X_train, X_test, y_train)
    clf_entropy = tarin_using_entropy(X_train, X_test, y_train)

    # Operational Phase
    print("Results Using Gini Index:")

    # Prediction using gini
    y_pred_gini = prediction(X_test, clf_gini)
    cal_accuracy(y_test, y_pred_gini)

    print("Results Using Entropy:")
    # Prediction using entropy
    y_pred_entropy = prediction(X_test, clf_entropy)
    cal_accuracy(y_test, y_pred_entropy)
```

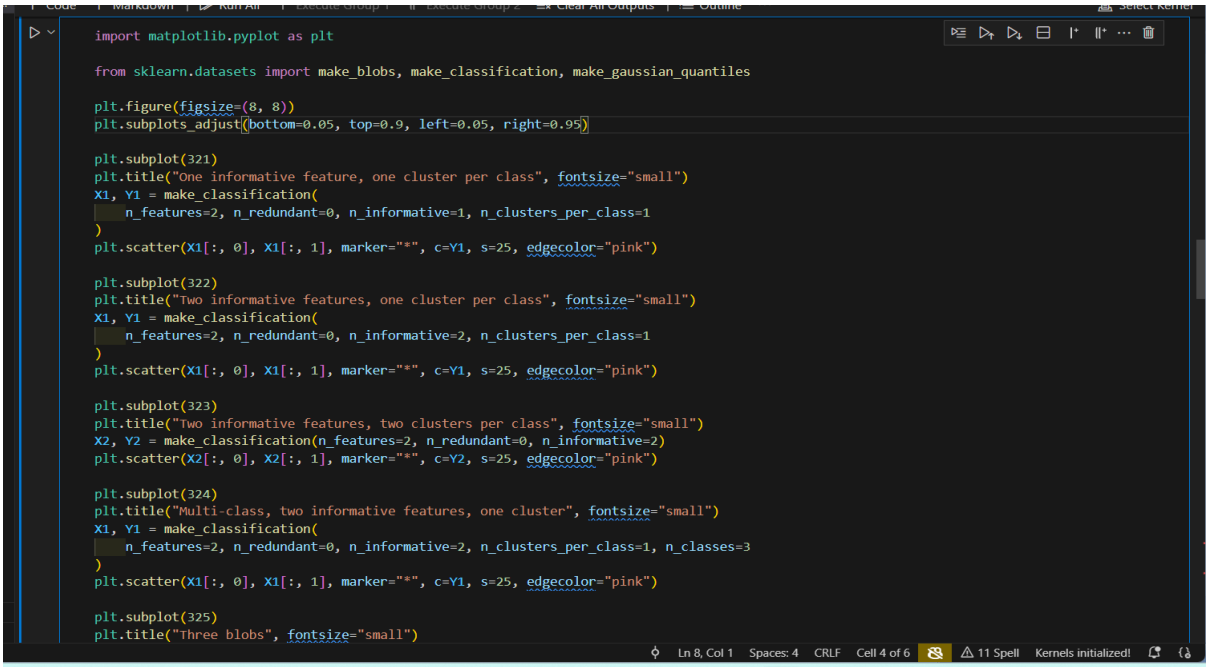


```
Dataset Length:  4999
Dataset Shape:  (4999, 31)
Dataset:     Time        V1        V2        V3        V4        V5        V6        V7  \
0     0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
1     0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
2     1 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
3     1 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
4     2 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

         V8        V9  ...       V21       V22       V23       V24       V25  \
0  0.098698  0.363787  ... -0.018307  0.277838 -0.110474  0.066928  0.128539
1  0.085102 -0.255425  ... -0.225775 -0.638672  0.101288 -0.339846  0.167170
2  0.247676 -1.514654  ...  0.247998  0.771679  0.909412 -0.689281 -0.327642
3  0.377436 -1.387024  ... -0.108300  0.005274 -0.190321 -1.175575  0.647376
4 -0.270533  0.817739  ... -0.009431  0.798278 -0.137458  0.141267 -0.206010

        V26       V27       V28  Amount  Class
0 -0.189115  0.133558 -0.021053  149.62      0
1  0.125895 -0.008983  0.014724    2.69      0
2 -0.139097 -0.055353 -0.059752  378.66      0
3 -0.221929  0.062723  0.061458  123.50      0
4  0.502292  0.219422  0.215153   69.99      0

[5 rows x 31 columns]
Results Using Gini Index:
Predicted values:
[2270. 2270. 2270. ... 2270. 3770. 2270.]
Confusion Matrix:  [[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]
```

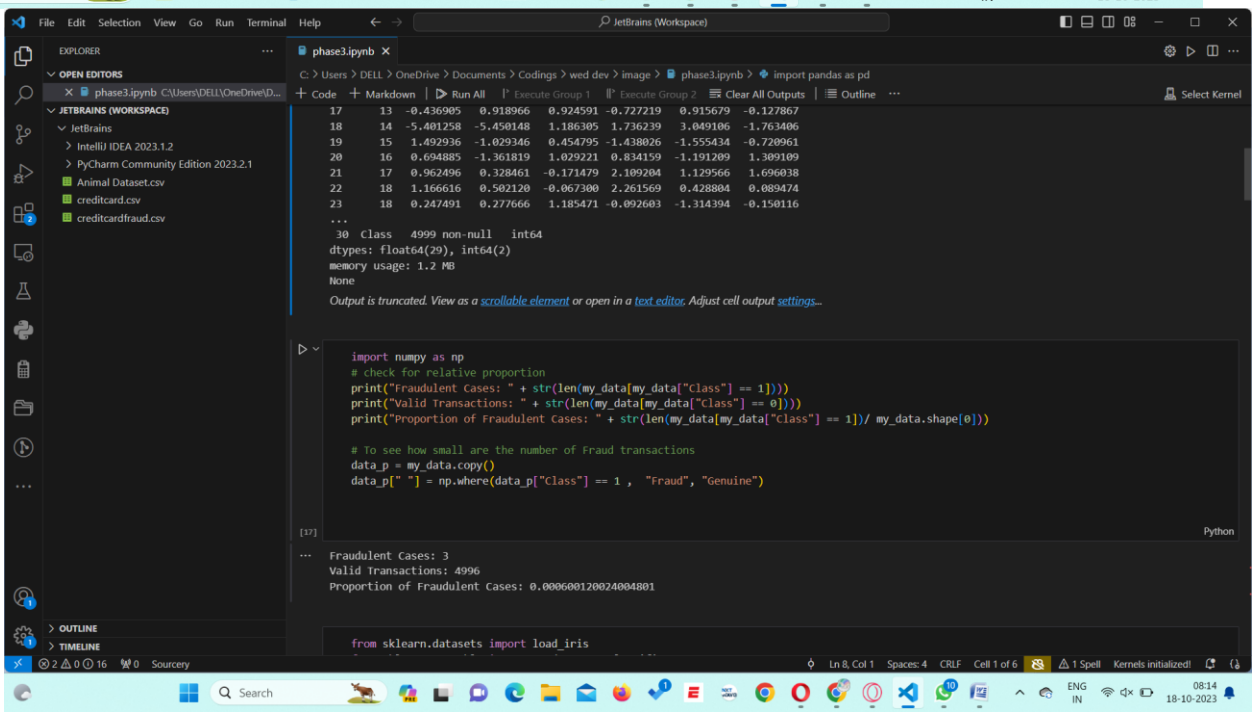


3. CREDITCARD FRAUD CSV IMPORT





```
import matplotlib.pyplot as plt

from sklearn.datasets import make_blobs, make_classification, make_gaussian_quantiles

plt.figure(figsize=(8, 8))
plt.subplots_adjust(bottom=0.05, top=0.9, left=0.05, right=0.95)

plt.subplot(321)
plt.title("One informative feature, one cluster per class", fontsize="small")
X1, Y1 = make_classification(
    n_features=2, n_redundant=0, n_informative=1, n_clusters_per_class=1
)
plt.scatter(X1[:, 0], X1[:, 1], marker="*", c=Y1, s=25, edgecolor="pink")

plt.subplot(322)
plt.title("Two informative features, one cluster per class", fontsize="small")
X1, Y1 = make_classification(
    n_features=2, n_redundant=0, n_informative=2, n_clusters_per_class=1
)
plt.scatter(X1[:, 0], X1[:, 1], marker="*", c=Y1, s=25, edgecolor="pink")

plt.subplot(323)
plt.title("Two informative features, two clusters per class", fontsize="small")
X2, Y2 = make_classification(n_features=2, n_redundant=0, n_informative=2)
plt.scatter(X2[:, 0], X2[:, 1], marker="*", c=Y2, s=25, edgecolor="pink")

plt.subplot(324)
plt.title("Multi-class, two informative features, one cluster", fontsize="small")
X1, Y1 = make_classification(
    n_features=2, n_redundant=0, n_informative=2, n_clusters_per_class=1, n_classes=3
)
plt.scatter(X1[:, 0], X1[:, 1], marker="*", c=Y1, s=25, edgecolor="pink")

plt.subplot(325)
plt.title("Three blobs", fontsize="small")
```



```
    17      13  -0.436905   0.918966   0.924591 -0.727219   0.915679  -0.127867
    18      14  -5.401258  -5.450148   1.186305  1.736239   3.049106  -1.763406
    19      15   1.492936  -1.029346   0.454795 -1.438026  -1.555434  -0.720961
    20      16   0.694885  -1.361819   1.029221  0.834159  -1.191209   1.309109
    21      17   0.962496   0.328461  -0.171479  2.109204   1.129566   1.696038
    22      18   1.166616   0.502120  -0.067300  2.261569   0.428804   0.089474
    23      18   0.247491   0.277666   1.185471 -0.092603  -1.314394  -0.150116
    ...
     30  Class   4999 non-null   int64
    dtypes: float64(29), int64(2)
    memory usage: 1.2 MB
    None
```

Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...

```
import numpy as np
# check for relative proportion
print("Fraudulent Cases: " + str(len(my_data[my_data["Class"] == 1])))
print("Valid Transactions: " + str(len(my_data[my_data["Class"] == 0])))
print("Proportion of Fraudulent Cases: " + str(len(my_data[my_data["Class"] == 1])/ my_data.shape[0]))

# To see how small are the number of Fraud transactions
data_p = my_data.copy()
data_p[" "] = np.where(data_p["Class"] == 1 ,  "Fraud", "Genuine")
```

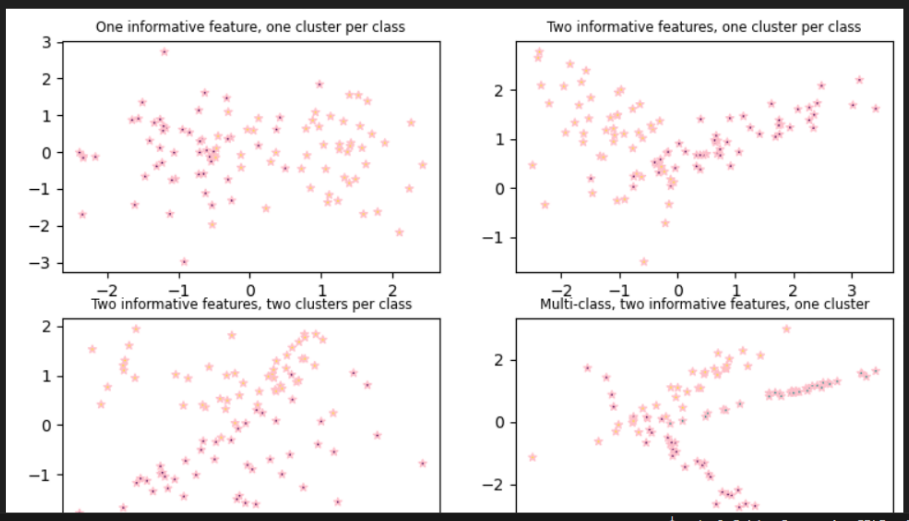
[17] Python

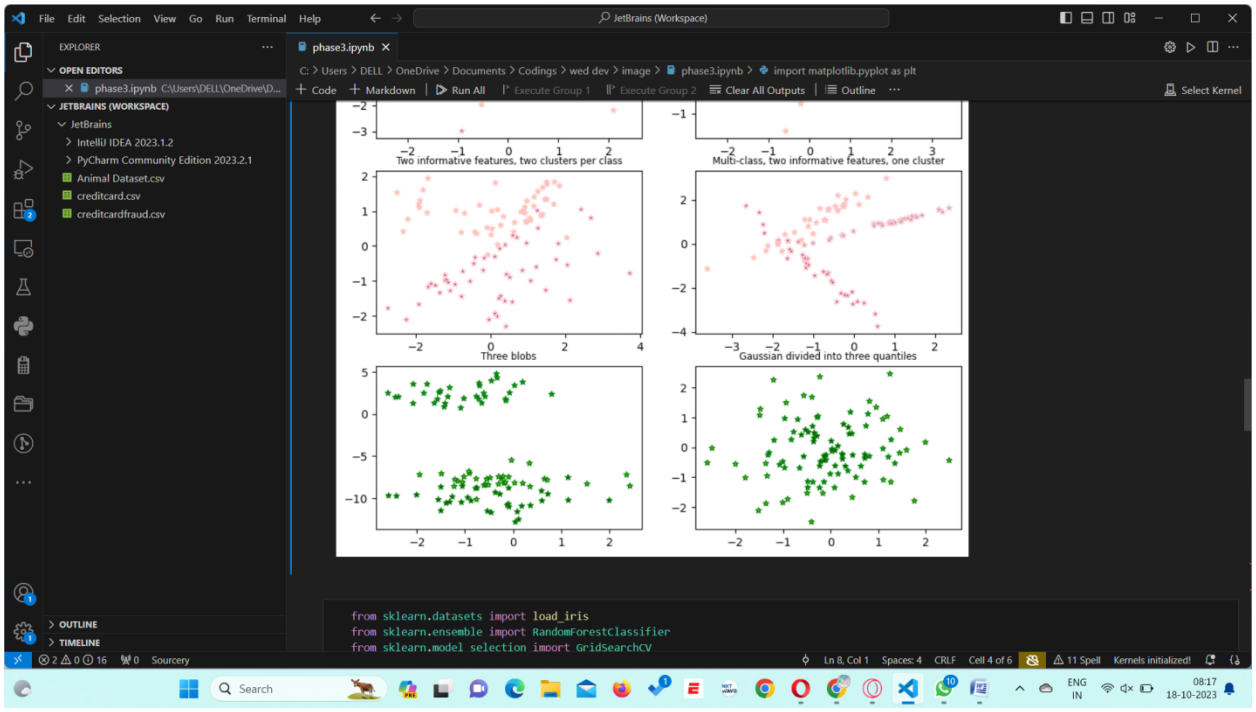
```
Fraudulent Cases: 3
Valid Transactions: 4996
Proportion of Fraudulent Cases: 0.000600120024004801
```

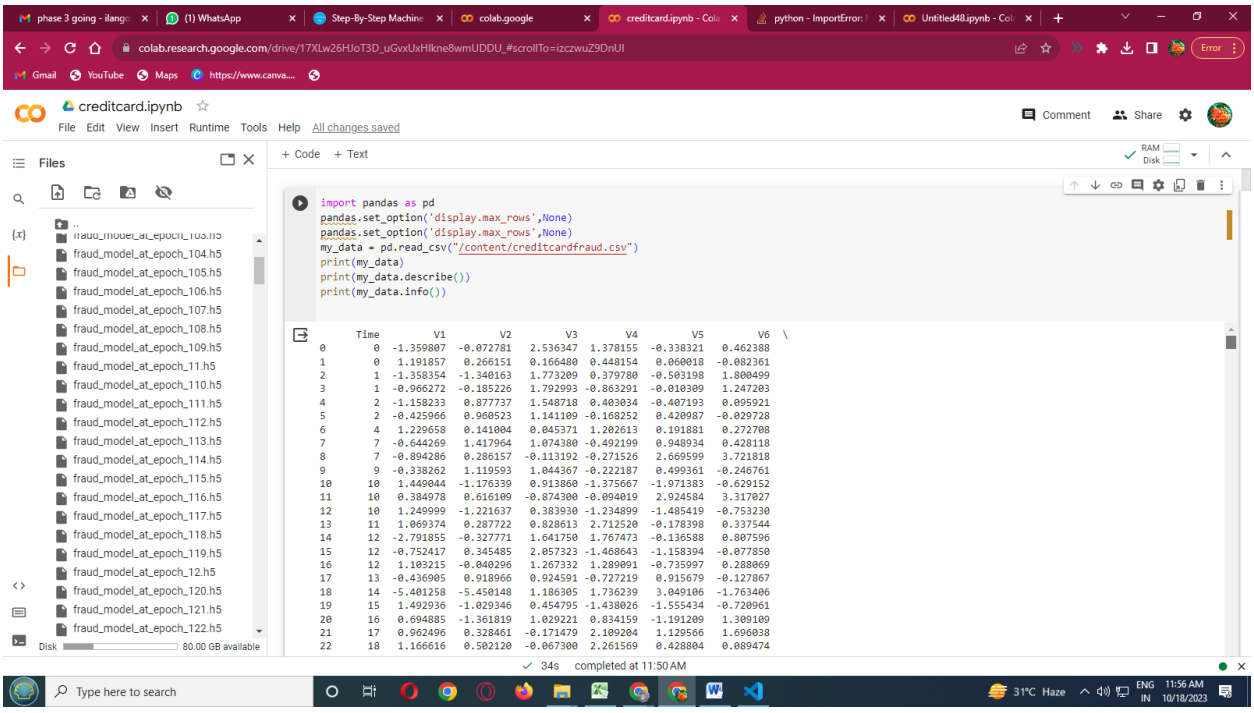
```
from sklearn.datasets import load_iris
```

```
plt.subplot(325)
plt.title("Three blobs", fontsize="small")
X1, Y1 = make_blobs(n_features=2, centers=3)
plt.scatter(X1[:, 0], X1[:, 1], marker="*", c=Y1, s=25, edgecolor="green")

plt.subplot(326)
plt.title("Gaussian divided into three quantiles", fontsize="small")
X1, Y1 = make_gaussian_quantiles(n_features=2, n_classes=3)
plt.scatter(X1[:, 0], X1[:, 1], marker="*", c=Y1, s=25, edgecolor="green")

plt.show()
```

[16]






creditcard.ipynb
File Edit View Insert Runtime Tools Help All changes saved
Comment Share
Files
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import pandas as pd
pandas.set_option('display.max_rows',None)
pandas.set_option('display.max_rows',None)
my_data = pd.read_csv("/content/creditcardfraud.csv")
print(my_data)
print(my_data.describe())
print(my_data.info())
Time V1 V2 V3 V4 V5 V6 \
0 0 -1.359807 -0.072781 2.536347 1.378155 -0.338321 0.462388
1 0 1.191857 0.266151 0.166480 0.448154 0.060018 -0.082361
2 1 -1.358354 -1.340163 1.773209 0.379780 -0.503198 1.800499
3 1 -0.966272 -0.185226 1.792993 -0.863291 -0.010309 1.247203
4 2 -1.158233 0.877737 1.548718 0.403034 -0.407193 0.095921
5 2 -0.425966 0.960523 1.141109 -0.168252 0.420987 -0.029728
6 4 1.229658 0.141004 0.045371 1.202613 0.191881 0.272708
7 7 -0.644269 1.417964 1.074380 -0.492199 0.948934 0.428118
8 7 -0.894286 0.286157 -0.113192 -0.271526 2.669599 3.721818
9 9 -0.338262 1.119593 1.044367 -0.222187 0.499361 -0.246761
10 10 1.449044 -1.176339 0.913860 -1.375667 -1.971383 -0.629152
11 10 0.384978 0.616109 -0.874300 -0.094019 2.924584 3.317027
12 10 1.249999 -1.221637 0.383930 -1.234899 -1.485419 -0.753230
13 11 1.069374 0.287722 0.828613 2.712520 -0.178398 0.337544
14 12 -2.791855 -0.327771 1.641750 1.767473 -0.136588 0.807596
15 12 -0.752417 0.345485 2.057323 -1.468643 -1.158394 -0.077850
16 12 1.103215 -0.040296 1.267332 1.289091 -0.735997 0.288069
17 13 -0.436905 0.918966 0.924591 -0.727219 0.915679 -0.127867
18 14 -5.401258 -5.450148 1.186305 1.736239 3.049106 -1.763406
19 15 1.492936 -1.029346 0.454795 -1.438026 -1.555434 -0.720961
20 16 0.694885 -1.361819 1.029221 0.834159 -1.191209 1.309109
21 17 0.962496 0.328461 -0.171479 2.109204 1.129566 1.696038
22 18 1.166616 0.502120 -0.067300 2.261569 0.428804 0.089474
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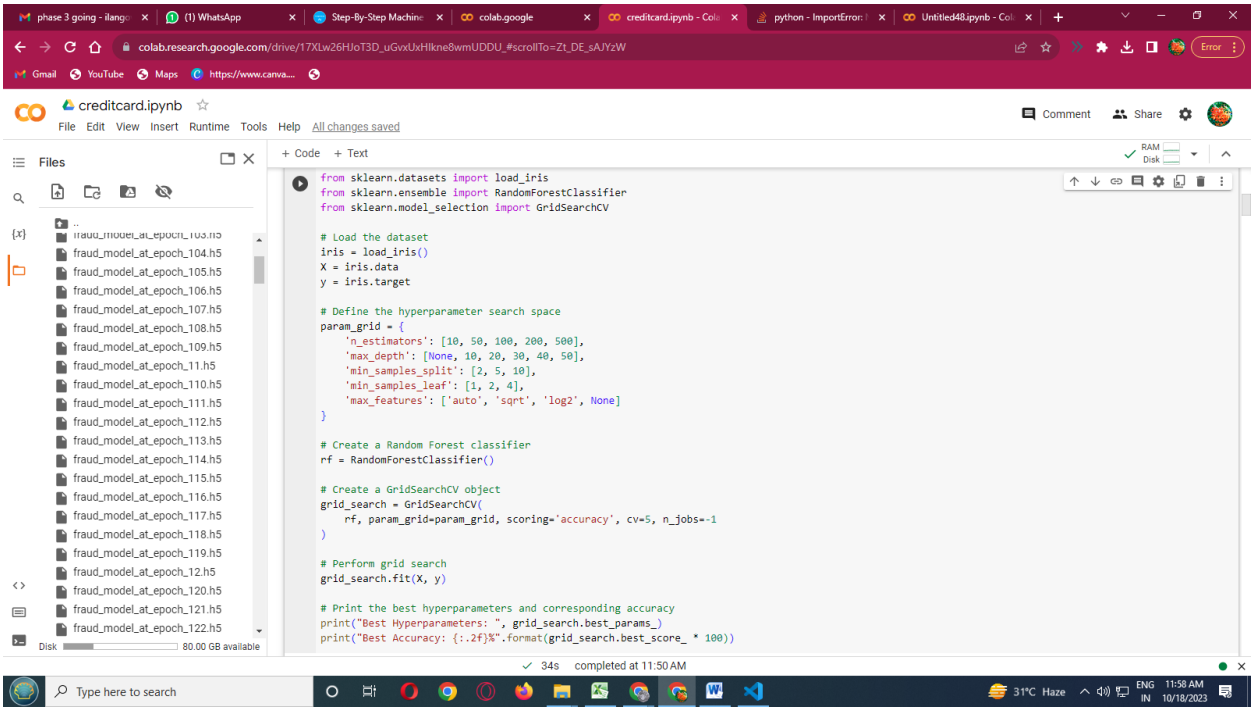
ENG IN 11:56 AM 10/18/2023


creditcard.ipynb
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Files
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from sklearn.datasets import load_iris
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
# Load the dataset
iris = load_iris()
X = iris.data
y = iris.target
# Define the hyperparameter search space
param_grid = {
'n_estimators': [10, 50, 100, 200, 500],
'max_depth': [None, 10, 20, 30, 40, 50],
'min_samples_split': [2, 5, 10],
'min_samples_leaf': [1, 2, 4],
'max_features': ['auto', 'sqrt', 'log2', None]
}
# Create a Random Forest classifier
rf = RandomForestClassifier()
# Create a GridSearchCV object
grid_search = GridSearchCV(
rf, param_grid=param_grid, scoring='accuracy', cv=5, n_jobs=-1
)
# Perform grid search
grid_search.fit(X, y)
# Print the best hyperparameters and corresponding accuracy
print("Best Hyperparameters: ", grid_search.best_params_)
print("Best Accuracy: {:.2f}%".format(grid_search.best_score_ * 100))
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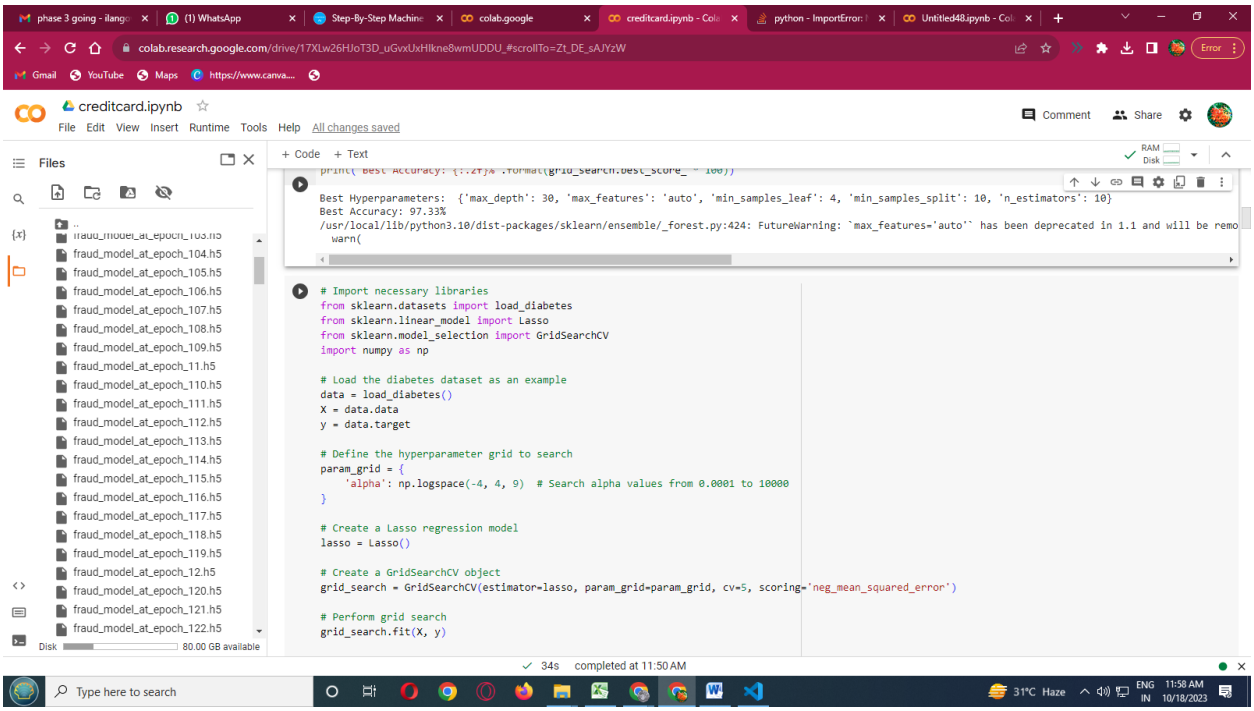
creditcard.ipynb
File Edit View Insert Runtime Tools Help All changes saved
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Files
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Best Hyperparameters: {'max_depth': 30, 'max_features': 'auto', 'min_samples_leaf': 4, 'min_samples_split': 10, 'n_estimators': 10}
Best Accuracy: 97.33%
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_forest.py:424: FutureWarning: `max_features='auto'` has been deprecated in 1.1 and will be remo
warn(
# Import necessary libraries
from sklearn.datasets import load_diabetes
from sklearn.linear_model import Lasso
from sklearn.model_selection import GridSearchCV
import numpy as np
# Load the diabetes dataset as an example
data = load_diabetes()
X = data.data
y = data.target
# Define the hyperparameter grid to search
param_grid = {
'alpha': np.logspace(-4, 4, 9) # Search alpha values from 0.0001 to 10000
}
# Create a Lasso regression model
lasso = Lasso()
# Create a GridSearchCV object
grid_search = GridSearchCV(estimator=lasso, param_grid=param_grid, cv=5, scoring='neg_mean_squared_error')
# Perform grid search
grid_search.fit(X, y)
fraud_model_at_epoch_104.h5
fraud_model_at_epoch_105.h5
fraud_model_at_epoch_106.h5
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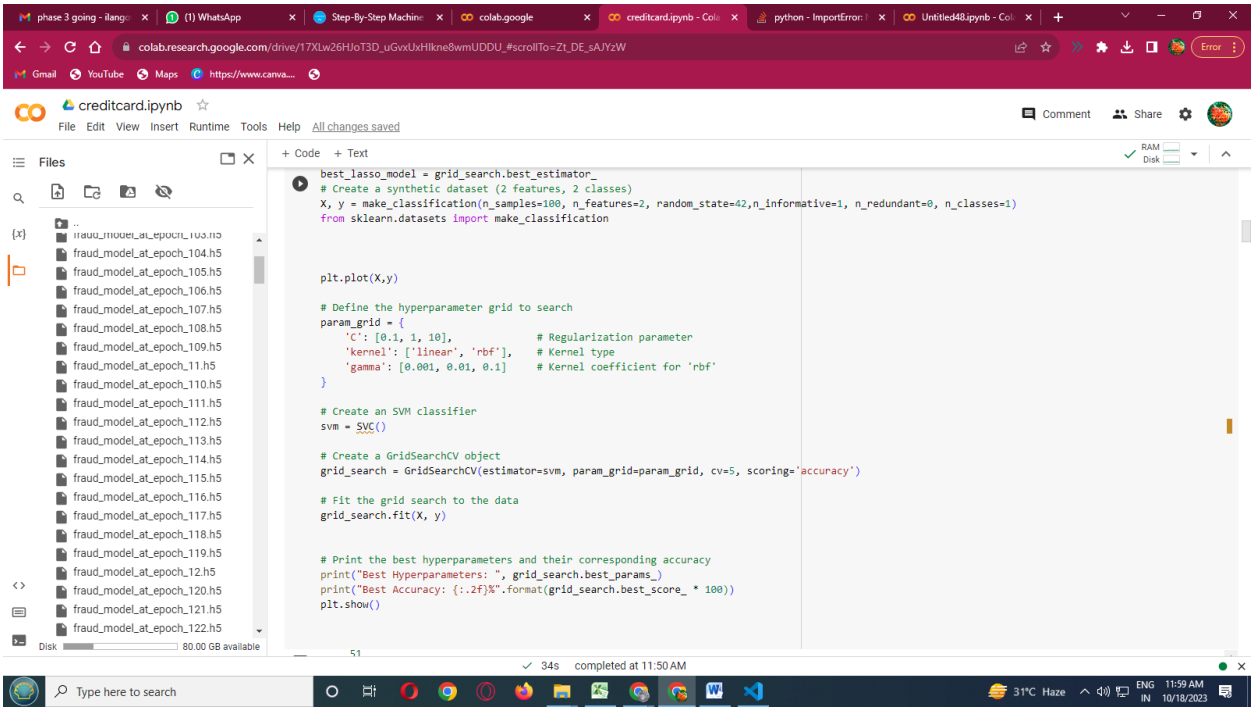
creditcard.ipynb
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best_lasso_model = grid_search.best_estimator_
# Create a synthetic dataset (2 features, 2 classes)
X, y = make_classification(n_samples=100, n_features=2, random_state=42,n_informative=1, n_redundant=0, n_classes=1)
from sklearn.datasets import make_classification
plt.plot(X,y)
# Define the hyperparameter grid to search
param_grid = {
'C': [0.1, 1, 10], # Regularization parameter
'kernel': ['linear', 'rbf'], # Kernel type
'gamma': [0.001, 0.01, 0.1] # Kernel coefficient for 'rbf'
}
# Create an SVM classifier
svm = SVC()
# Create a GridSearchCV object
grid_search = GridSearchCV(estimator=svm, param_grid=param_grid, cv=5, scoring='accuracy')
# Fit the grid search to the data
grid_search.fit(X, y)
# Print the best hyperparameters and their corresponding accuracy
print("Best Hyperparameters: ", grid_search.best_params_)
print("Best Accuracy: {:.2f}%".format(grid_search.best_score_ * 100))
plt.show()
fraud_model_at_epoch_104.h5
fraud_model_at_epoch_105.h5
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fraud_model_at_epoch_107.h5
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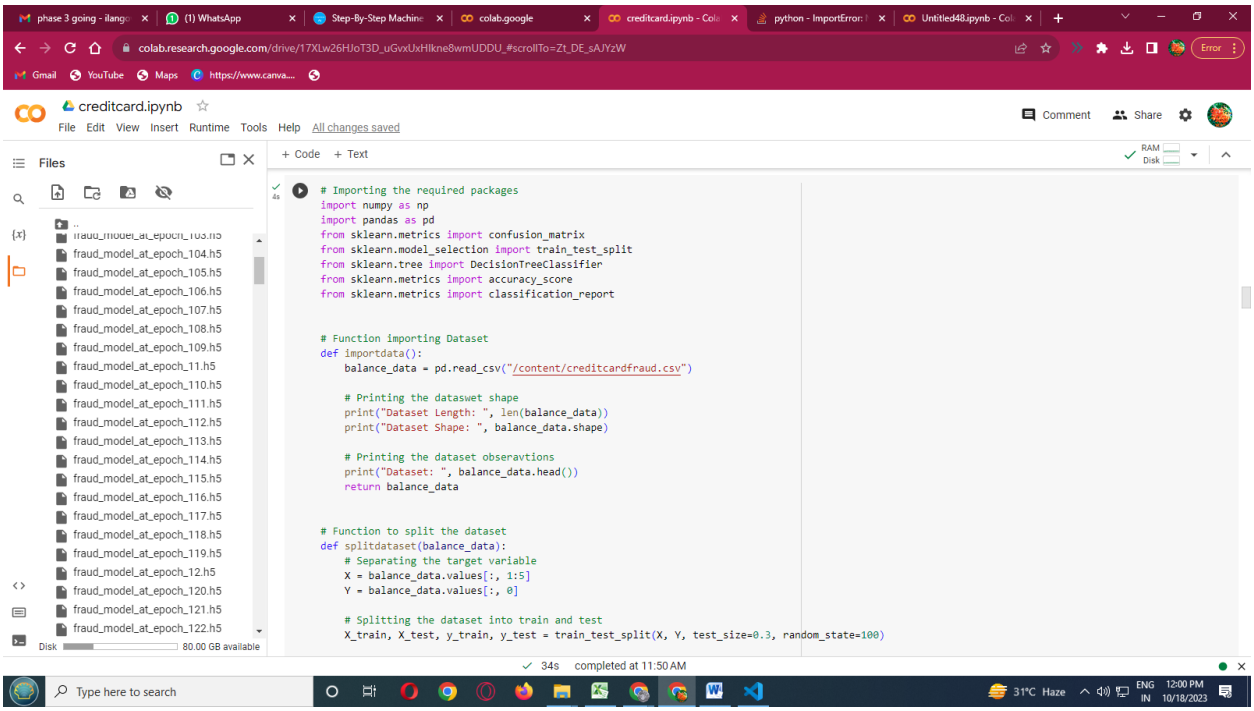
creditcard.ipynb
File Edit View Insert Runtime Tools Help All changes saved
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Files
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# Importing the required packages
import numpy as np
import pandas as pd
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
# Function importing Dataset
def importdata():
balance_data = pd.read_csv("/content/creditcardfraud.csv")
# Printing the dataswet shape
print("Dataset Length: ", len(balance_data))
print("Dataset Shape: ", balance_data.shape)
# Printing the dataset obseravtions
print("Dataset: ", balance_data.head())
return balance_data
# Function to split the dataset
def splitdataset(balance_data):
# Separating the target variable
X = balance_data.values[:, 1:5]
Y = balance_data.values[:, 0]
# Splitting the dataset into train and test
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3, random_state=100)
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fraud_model_at_epoch_106.h5
fraud_model_at_epoch_107.h5
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fraud_model_at_epoch_109.h5
fraud_model_at_epoch_11.h5
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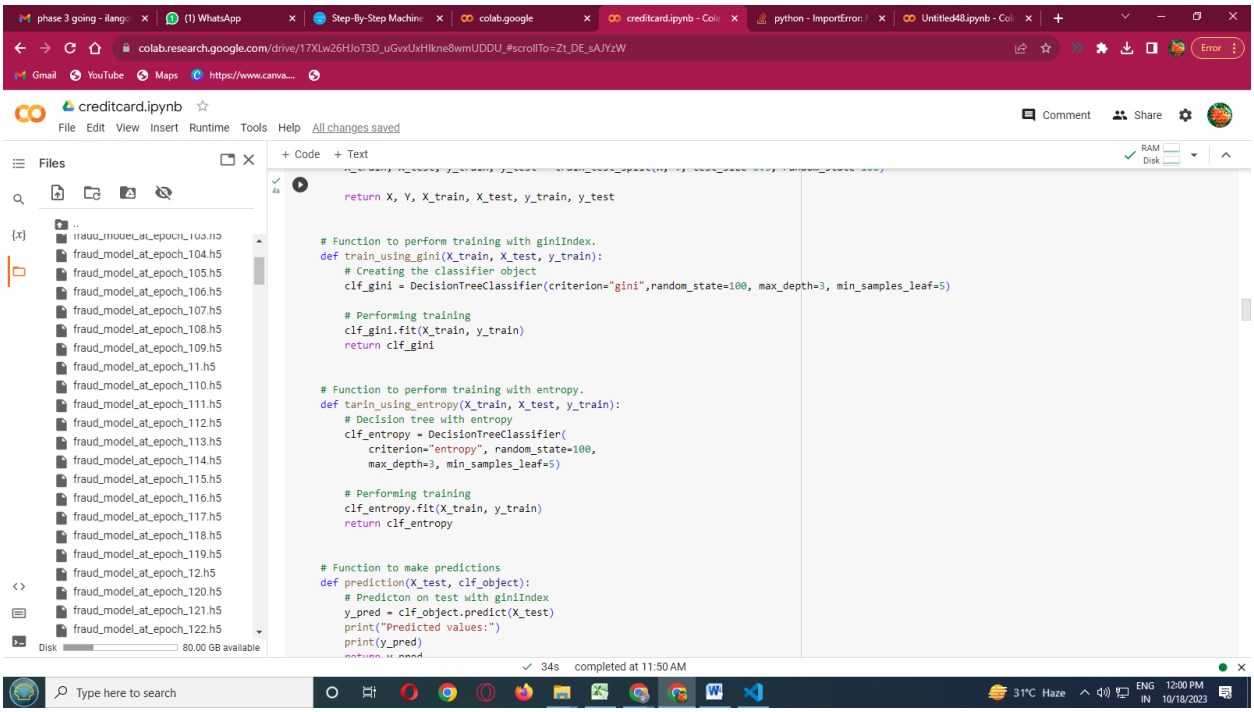
creditcard.ipynb
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Comment Share
Files
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return X, Y, X_train, X_test, y_train, y_test
# Function to perform training with giniIndex.
def train_using_gini(X_train, X_test, y_train):
# Creating the classifier object
clf_gini = DecisionTreeClassifier(criterion="gini",random_state=100, max_depth=3, min_samples_leaf=5)
# Performing training
clf_gini.fit(X_train, y_train)
return clf_gini
# Function to perform training with entropy.
def tarin_using_entropy(X_train, X_test, y_train):
# Decision tree with entropy
clf_entropy = DecisionTreeClassifier(
criterion="entropy", random_state=100,
max_depth=3, min_samples_leaf=5)
# Performing training
clf_entropy.fit(X_train, y_train)
return clf_entropy
# Function to make predictions
def prediction(X_test, clf_object):
# Predicton on test with giniIndex
y_pred = clf_object.predict(X_test)
print("Predicted values:")
print(y_pred)
fraud_model_at_epoch_104.h5
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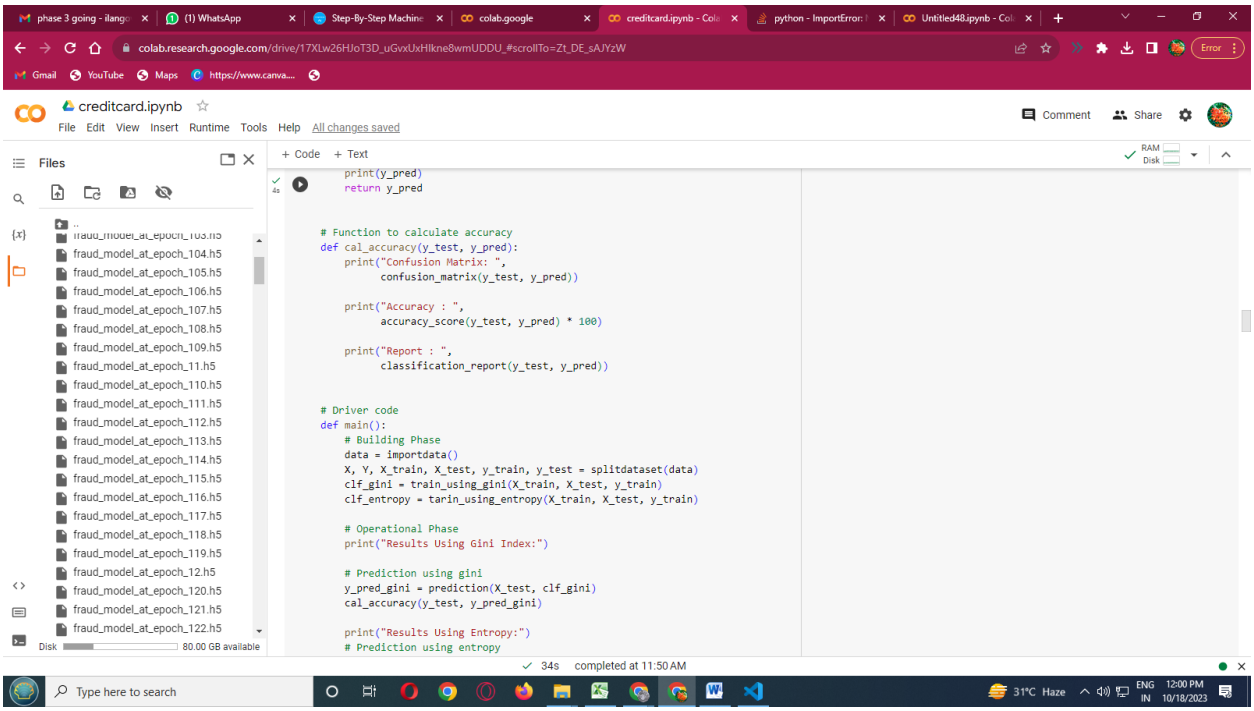
creditcard.ipynb
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Comment Share
Files
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print(y_pred)
return y_pred
# Function to calculate accuracy
def cal_accuracy(y_test, y_pred):
print("Confusion Matrix: ",
confusion_matrix(y_test, y_pred))
print("Accuracy : ",
accuracy_score(y_test, y_pred) * 100)
print("Report : ",
classification_report(y_test, y_pred))
# Driver code
def main():
# Building Phase
data = importdata()
X, Y, X_train, X_test, y_train, y_test = splitdataset(data)
clf_gini = train_using_gini(X_train, X_test, y_train)
clf_entropy = tarin_using_entropy(X_train, X_test, y_train)
# Operational Phase
print("Results Using Gini Index:")
# Prediction using gini
y_pred_gini = prediction(X_test, clf_gini)
cal_accuracy(y_test, y_pred_gini)
print("Results Using Entropy:")
# Prediction using entropy
fraud_model_at_epoch_104.h5
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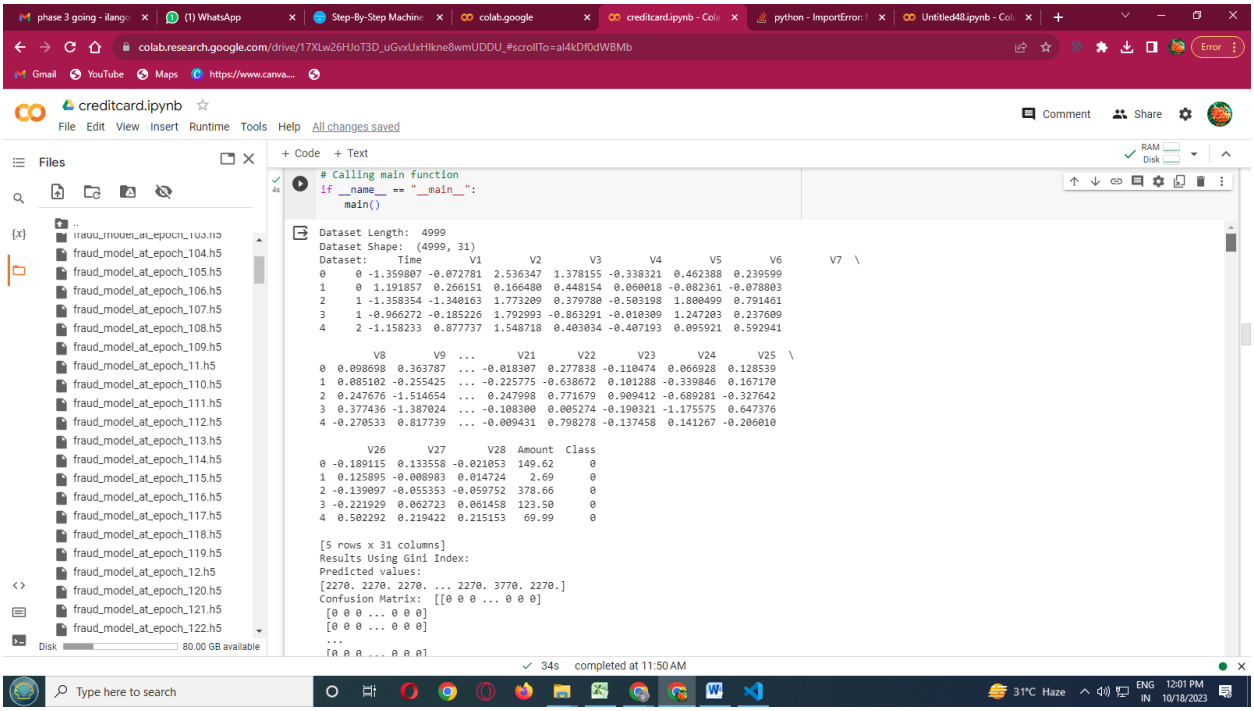
creditcard.ipynb
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# Calling main function
if __name__ == "__main__":
main()
Dataset Length: 4999
Dataset Shape: (4999, 31)
Dataset: Time V1 V2 V3 V4 V5 V6 V7 \
0 0 -1.359807 -0.072781 2.536347 1.378155 -0.338321 0.462388 0.239599
1 0 1.191857 0.266151 0.166480 0.448154 0.060018 -0.082361 -0.078803
2 1 -1.358354 -1.340163 1.773209 0.379780 -0.503198 1.800499 0.791461
3 1 -0.966272 -0.185226 1.792993 -0.863291 -0.010309 1.247203 0.237609
4 2 -1.158233 0.877737 1.548718 0.403034 -0.407193 0.095921 0.592941
V8 V9 ... V21 V22 V23 V24 V25 \
0 0.098698 0.363787 ... -0.018307 0.277838 -0.110474 0.066928 0.128539
1 0.085102 -0.255425 ... -0.225775 -0.638672 0.101288 -0.339846 0.167170
2 0.247676 -1.514654 ... 0.247998 0.771679 0.909412 -0.689281 -0.327642
3 0.377436 -1.387024 ... -0.108300 0.005274 -0.190321 -1.175575 0.647376
4 -0.270533 0.817739 ... -0.009431 0.798278 -0.137458 0.141267 -0.206010
V26 V27 V28 Amount Class
0 -0.189115 0.133558 -0.021053 149.62 0
1 0.125895 -0.008983 0.014724 2.69 0
2 -0.139097 -0.055353 -0.059752 378.66 0
3 -0.221929 0.062723 0.061458 123.50 0
4 0.502292 0.219422 0.215153 69.99 0
[5 rows x 31 columns]
Results Using Gini Index:
Predicted values:
[2270. 2270. 2270. ... 2270. 3770. 2270.]
Confusion Matrix: [[0 0 0 ... 0 0 0]
[0 0 0 ... 0 0 0]
[0 0 0 ... 0 0 0]
...
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fraud_model_at_epoch_105.h5
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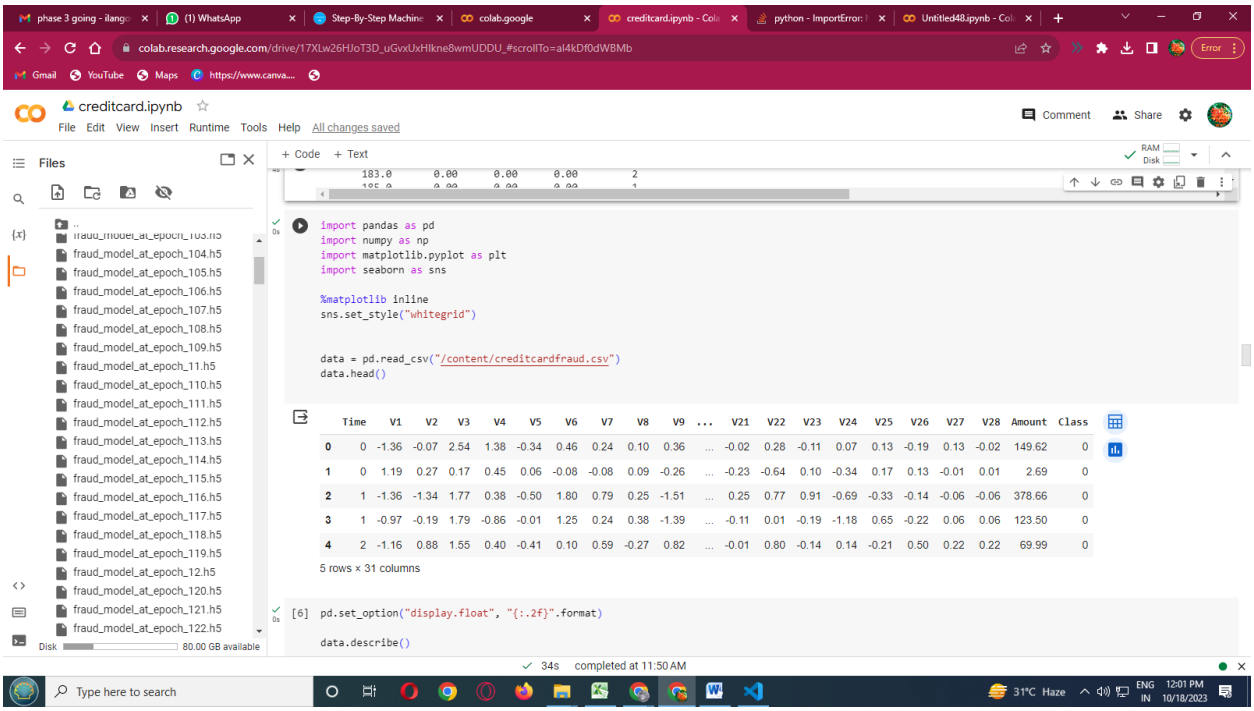

creditcard.ipynb

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

%matplotlib inline
sns.set_style("whitegrid")


data = pd.read_csv("/content/creditcardfraud.csv")
data.head()
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27	V28	Amount	Class
0	0	-1.36	-0.07	2.54	1.38	-0.34	0.46	0.24	0.10	0.36	...	-0.02	0.28	-0.11	0.07	0.13	-0.19	0.13	-0.02	149.62	0
1	0	1.19	0.27	0.17	0.45	0.06	-0.08	-0.08	0.09	-0.26	...	-0.23	-0.64	0.10	-0.34	0.17	0.13	-0.01	0.01	2.69	0
2	1	-1.36	-1.34	1.77	0.38	-0.50	1.80	0.79	0.25	-1.51	...	0.25	0.77	0.91	-0.69	-0.33	-0.14	-0.06	-0.06	378.66	0
3	1	-0.97	-0.19	1.79	-0.86	-0.01	1.25	0.24	0.38	-1.39	...	-0.11	0.01	-0.19	-1.18	0.65	-0.22	0.06	0.06	123.50	0
4	2	-1.16	0.88	1.55	0.40	-0.41	0.10	0.59	-0.27	0.82	...	-0.01	0.80	-0.14	0.14	-0.21	0.50	0.22	0.22	69.99	0

5 rows × 31 columns

```
[6] pd.set_option("display.float", "{:.2f}".format)

    data.describe()
```

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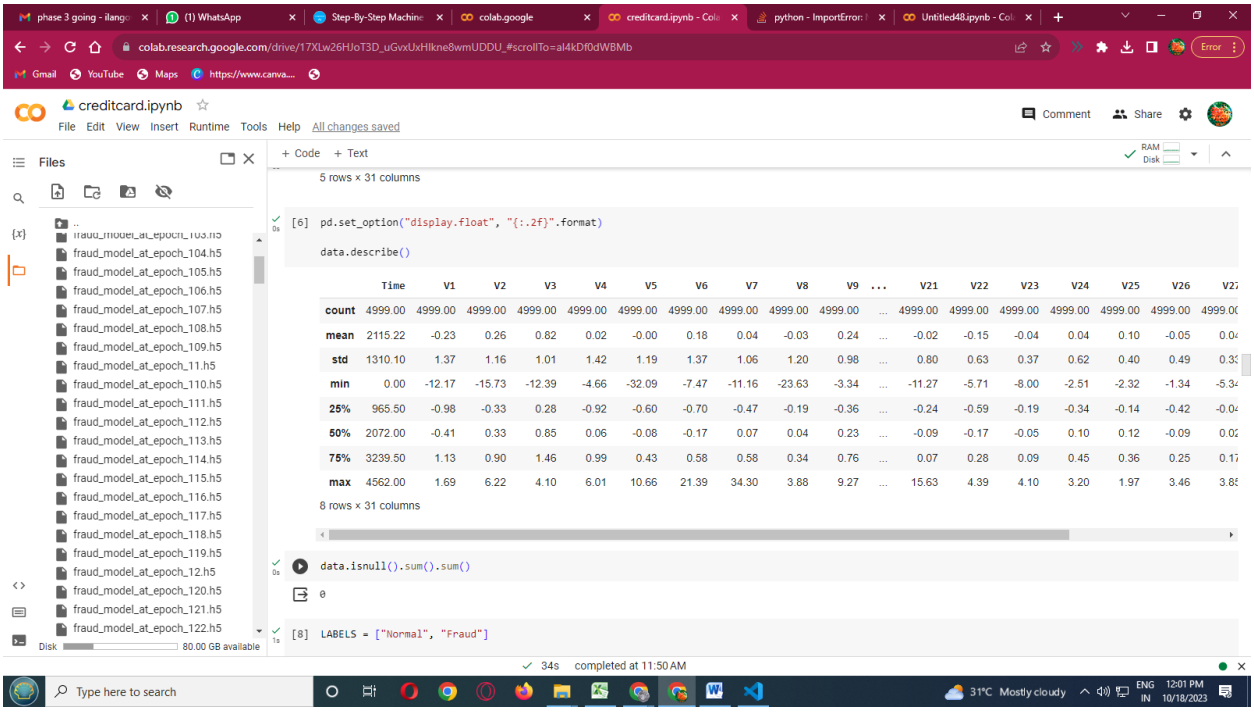

creditcard.ipynb

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5 rows × 31 columns

```
[6] pd.set_option("display.float", "{:.2f}".format)

    data.describe()
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27
count	4999.00	4999.00	4999.00	4999.00	4999.00	4999.00	4999.00	4999.00	4999.00	4999.00	...	4999.00	4999.00	4999.00	4999.00	4999.00	4999.00	4999.00
mean	2115.22	-0.23	0.26	0.82	0.02	-0.00	0.18	0.04	-0.03	0.24	...	-0.02	-0.15	-0.04	0.04	0.10	-0.05	0.04
std	1310.10	1.37	1.16	1.01	1.42	1.19	1.37	1.06	1.20	0.98	...	0.80	0.63	0.37	0.62	0.40	0.49	0.33
min	0.00	-12.17	-15.73	-12.39	-4.66	-32.09	-7.47	-11.16	-23.63	-3.34	...	-11.27	-5.71	-8.00	-2.51	-2.32	-1.34	-5.34
25%	965.50	-0.98	-0.33	0.28	-0.92	-0.60	-0.70	-0.47	-0.19	-0.36	...	-0.24	-0.59	-0.19	-0.34	-0.14	-0.42	-0.04
50%	2072.00	-0.41	0.33	0.85	0.06	-0.08	-0.17	0.07	0.04	0.23	...	-0.09	-0.17	-0.05	0.10	0.12	-0.09	0.02
75%	3239.50	1.13	0.90	1.46	0.99	0.43	0.58	0.58	0.34	0.76	...	0.07	0.28	0.09	0.45	0.36	0.25	0.17
max	4562.00	1.69	6.22	4.10	6.01	10.66	21.39	34.30	3.88	9.27	...	15.63	4.39	4.10	3.20	1.97	3.46	3.85

8 rows × 31 columns

```
    data.isnull().sum().sum()
```

```
0
```

```
[8] LABELS = ["Normal", "Fraud"]
```

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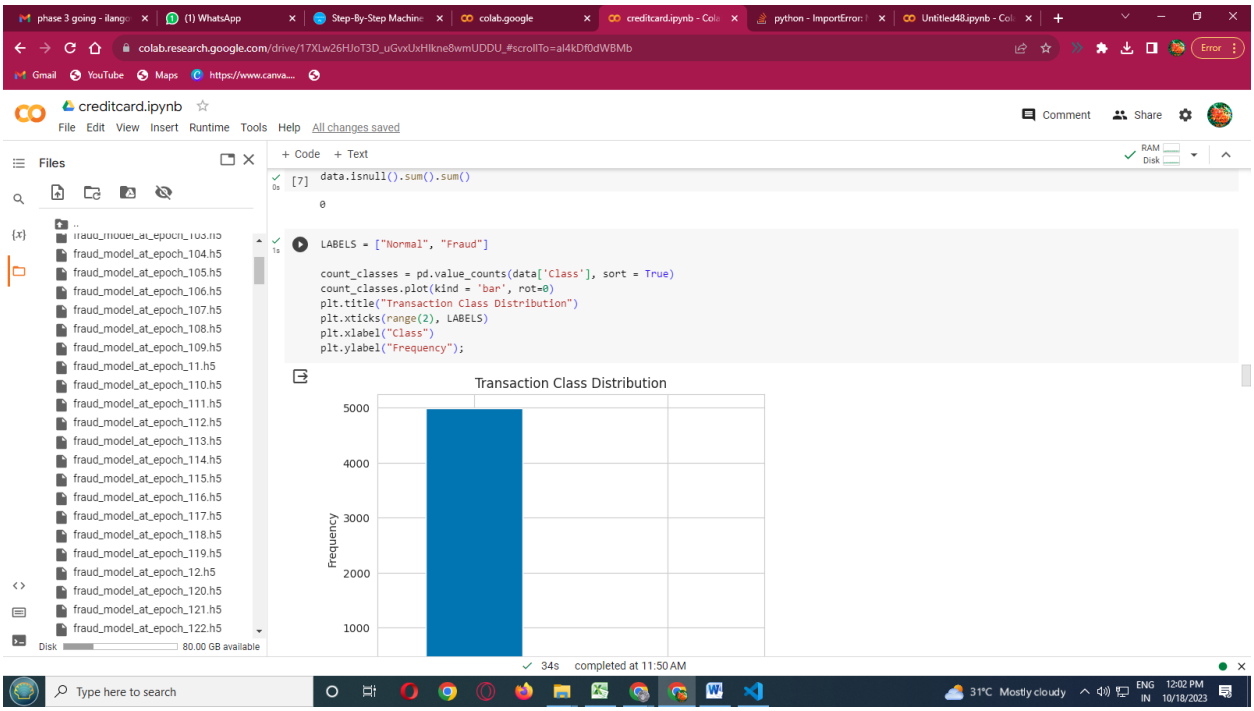
creditcard.ipynb
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[7] data.isnull().sum().sum()
0
LABELS = ["Normal", "Fraud"]
count_classes = pd.value_counts(data['Class'], sort = True)
count_classes.plot(kind = 'bar', rot=0)
plt.title("Transaction Class Distribution")
plt.xticks(range(2), LABELS)
plt.xlabel("Class")
plt.ylabel("Frequency");
Transaction Class Distribution
Frequency
5000
4000
3000
2000
1000
fraud_model_at_epoch_104.h5
fraud_model_at_epoch_105.h5
fraud_model_at_epoch_106.h5
fraud_model_at_epoch_107.h5
fraud_model_at_epoch_108.h5
fraud_model_at_epoch_109.h5
fraud_model_at_epoch_11.h5
fraud_model_at_epoch_110.h5
fraud_model_at_epoch_111.h5
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fraud_model_at_epoch_119.h5
fraud_model_at_epoch_12.h5
fraud_model_at_epoch_120.h5
fraud_model_at_epoch_121.h5
fraud_model_at_epoch_122.h5
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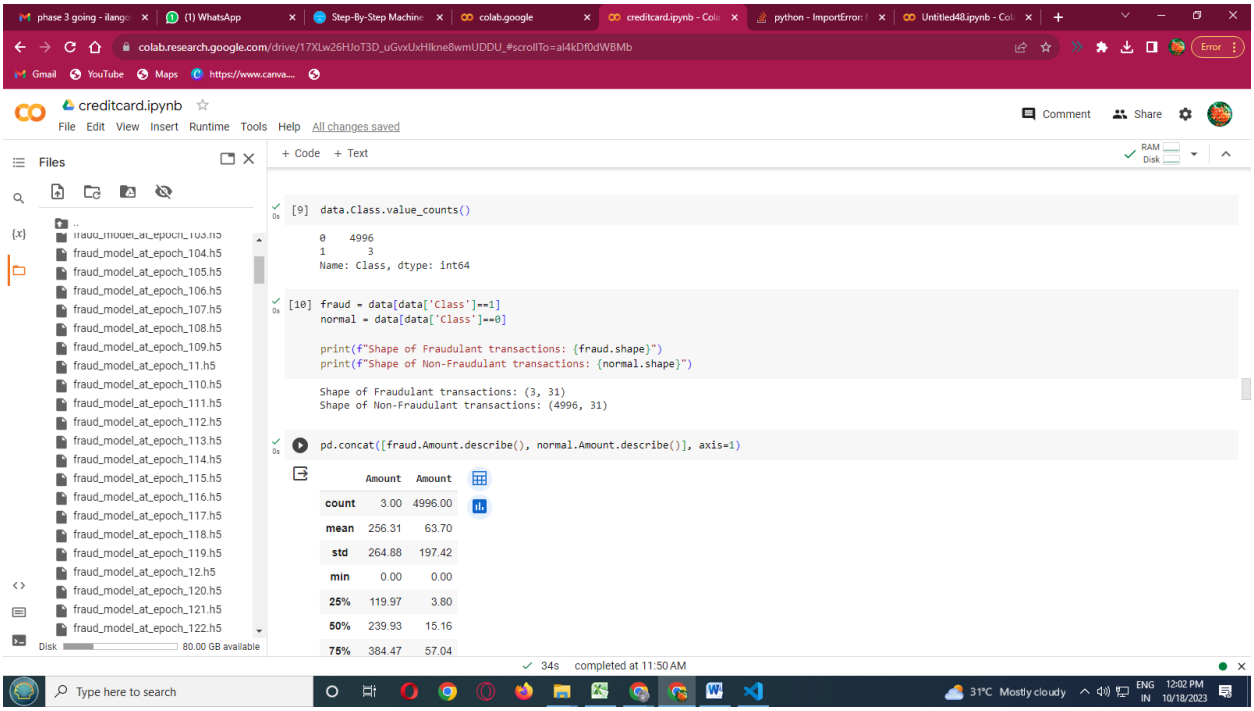
creditcard.ipynb
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[9] data.Class.value_counts()
0 4996
1 3
Name: Class, dtype: int64
[10] fraud = data[data['Class']==1]
normal = data[data['Class']==0]
print(f"Shape of Fraudulant transactions: {fraud.shape}")
print(f"Shape of Non-Fraudulant transactions: {normal.shape}")
Shape of Fraudulant transactions: (3, 31)
Shape of Non-Fraudulant transactions: (4996, 31)
pd.concat([fraud.Amount.describe(), normal.Amount.describe()], axis=1)
Amount Amount
count 3.00 4996.00
mean 256.31 63.70
std 264.88 197.42
min 0.00 0.00
25% 119.97 3.80
50% 239.93 15.16
75% 384.47 57.04
fraud_model_at_epoch_104.h5
fraud_model_at_epoch_105.h5
fraud_model_at_epoch_106.h5
fraud_model_at_epoch_107.h5
fraud_model_at_epoch_108.h5
fraud_model_at_epoch_109.h5
fraud_model_at_epoch_11.h5
fraud_model_at_epoch_110.h5
fraud_model_at_epoch_111.h5
fraud_model_at_epoch_112.h5
fraud_model_at_epoch_113.h5
fraud_model_at_epoch_114.h5
fraud_model_at_epoch_115.h5
fraud_model_at_epoch_116.h5
fraud_model_at_epoch_117.h5
fraud_model_at_epoch_118.h5
fraud_model_at_epoch_119.h5
fraud_model_at_epoch_12.h5
fraud_model_at_epoch_120.h5
fraud_model_at_epoch_121.h5
fraud_model_at_epoch_122.h5
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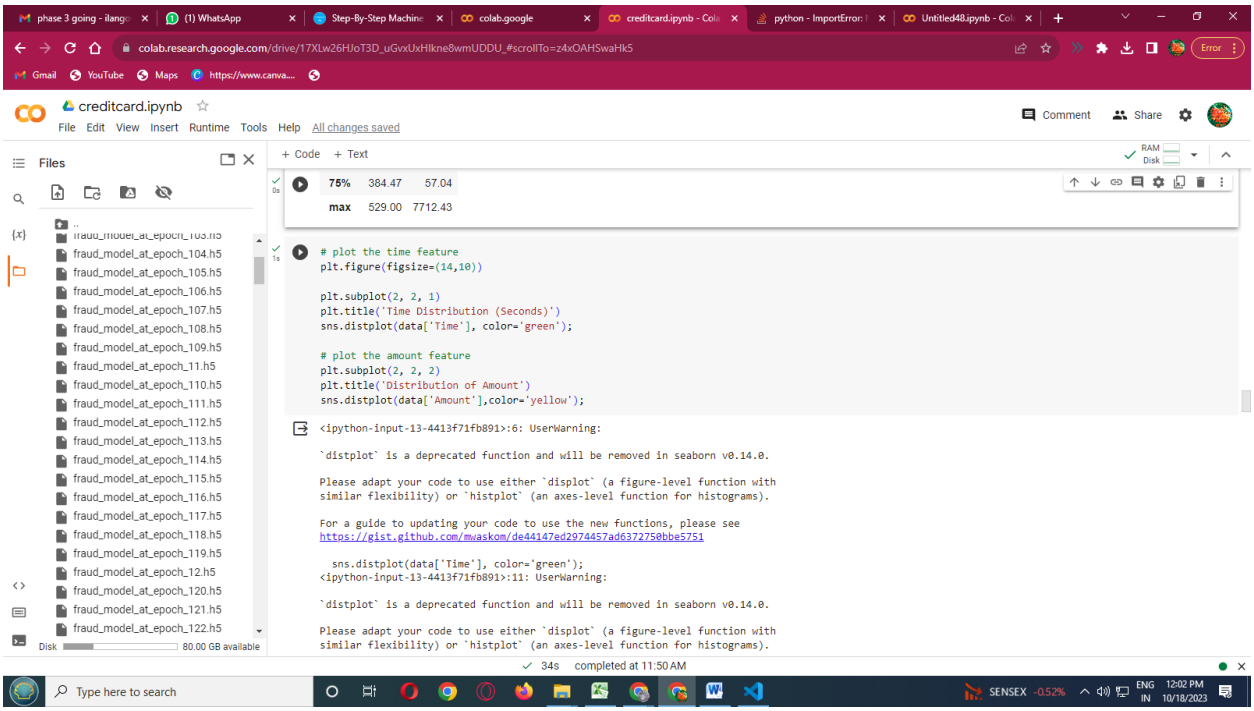
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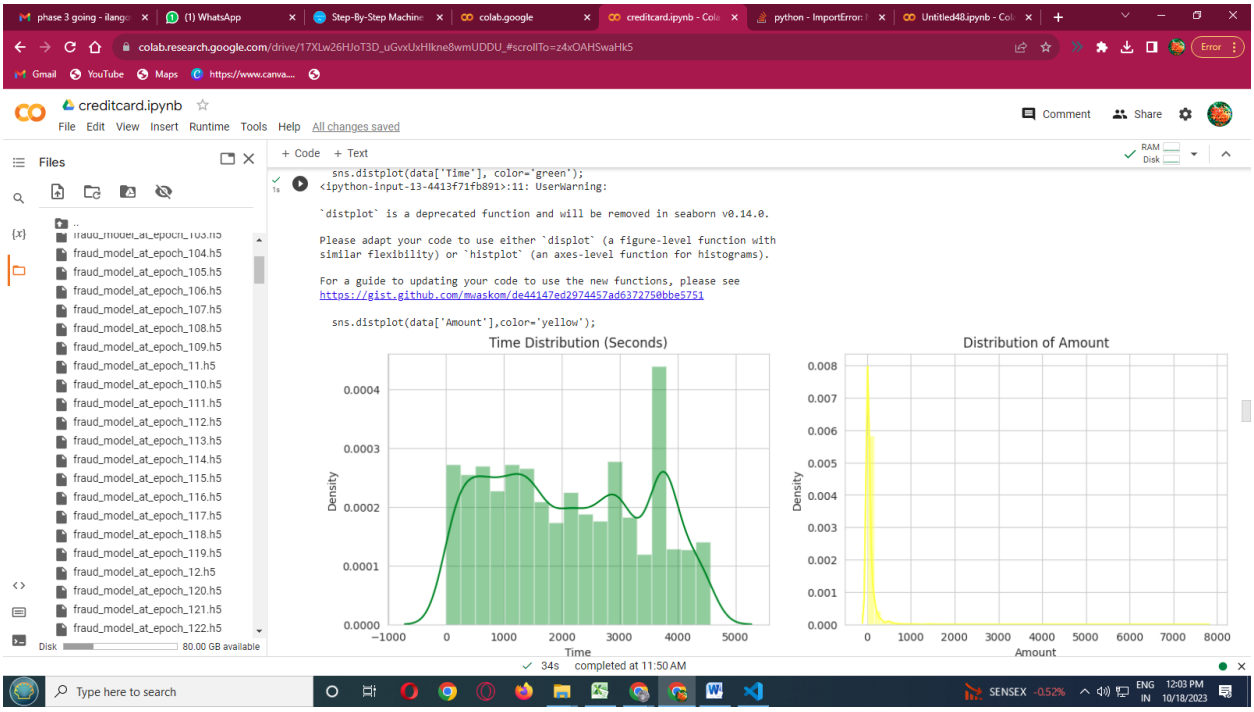
75% 384.47 57.04
max 529.00 7712.43
# plot the time feature
plt.figure(figsize=(14,10))
plt.subplot(2, 2, 1)
plt.title('Time Distribution (Seconds)')
sns.distplot(data['Time'], color='green');
# plot the amount feature
plt.subplot(2, 2, 2)
plt.title('Distribution of Amount')
sns.distplot(data['Amount'],color='yellow');
<ipython-input-13-4413f71fb891>:6: UserWarning:
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.
Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751
sns.distplot(data['Time'], color='green');
<ipython-input-13-4413f71fb891>:11: UserWarning:
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.
Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
34s completed at 11:50 AM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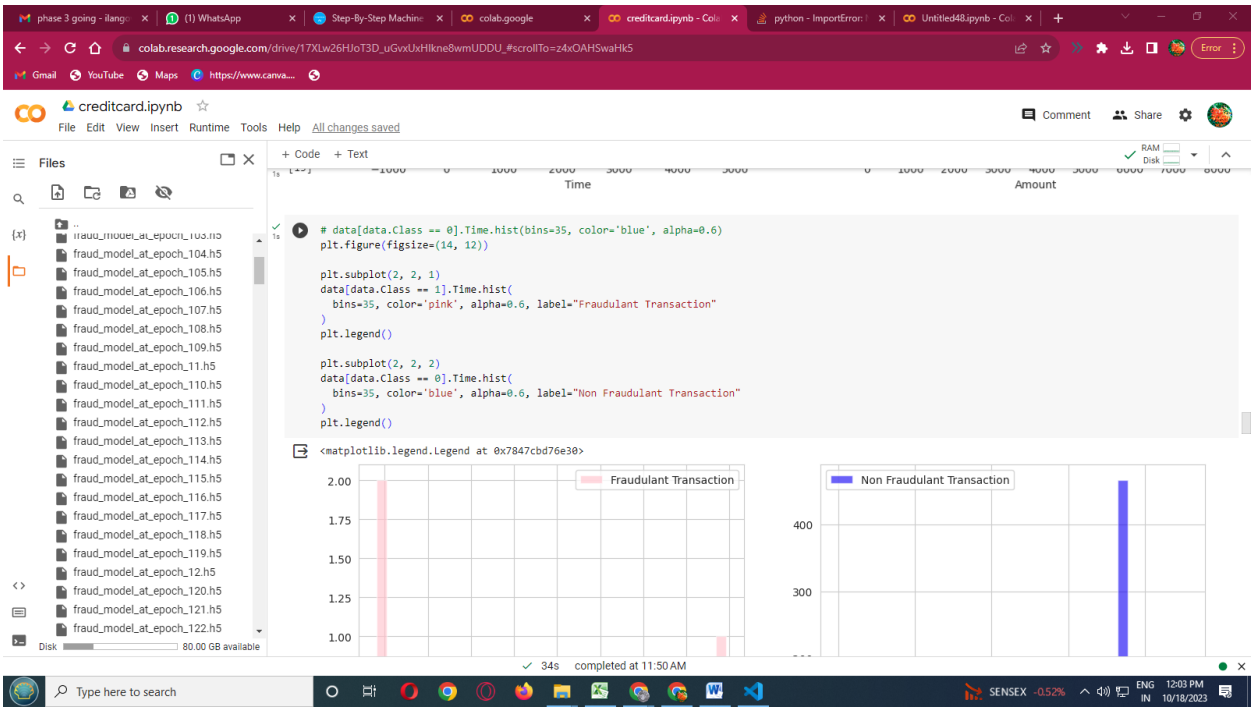
sns.distplot(data['Time'], color='green');
<ipython-input-13-4413f71fb891>:11: UserWarning:
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.
Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751
sns.distplot(data['Amount'],color='yellow');
Time Distribution (Seconds)
Density
Time
Distribution of Amount
Amount
34s completed at 11:50 AM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Time
Amount
# data[data.Class == 0].Time.hist(bins=35, color='blue', alpha=0.6)
plt.figure(figsize=(14, 12))
plt.subplot(2, 2, 1)
data[data.Class == 1].Time.hist(
bins=35, color='pink', alpha=0.6, label="Fraudulant Transaction"
)
plt.legend()
plt.subplot(2, 2, 2)
data[data.Class == 0].Time.hist(
bins=35, color='blue', alpha=0.6, label="Non Fraudulant Transaction"
)
plt.legend()
<matplotlib.legend.Legend at 0x7847cbd76e30>
Fraudulant Transaction
Non Fraudulant Transaction
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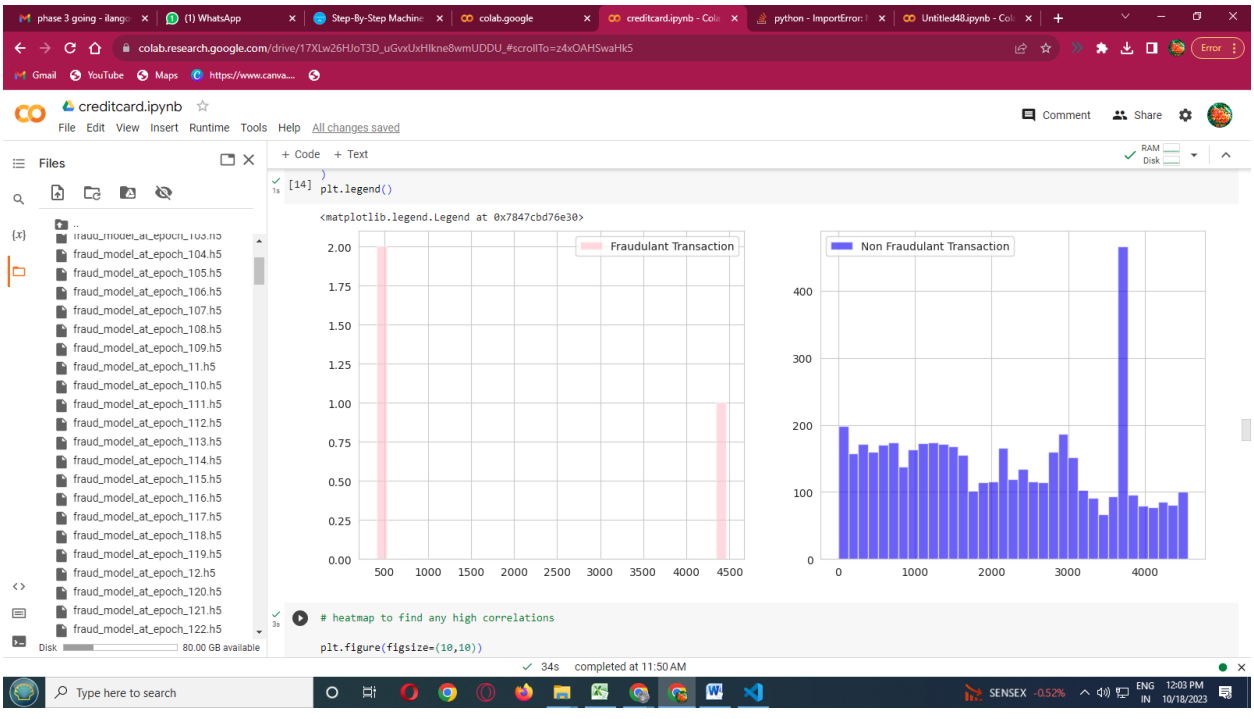
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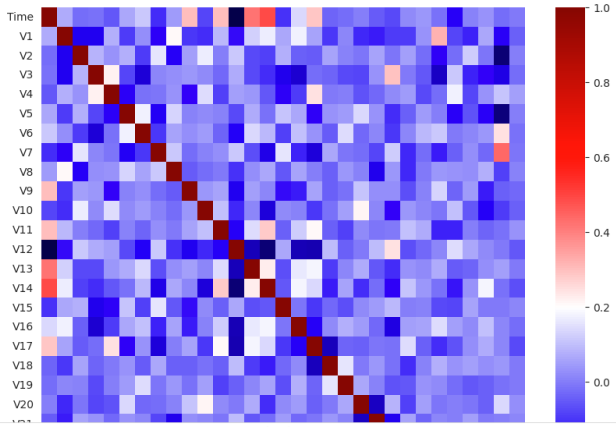
[14] plt.legend()
<matplotlib.legend.Legend at 0x7847cbd76e30>
Fraudulant Transaction
Non Fraudulant Transaction
# heatmap to find any high correlations
plt.figure(figsize=(10,10))
34s completed at 11:50 AM

```
plt.figure(figsize=(10,10))
sns.heatmap(data=data.corr(), cmap="seismic")
plt.show();
```

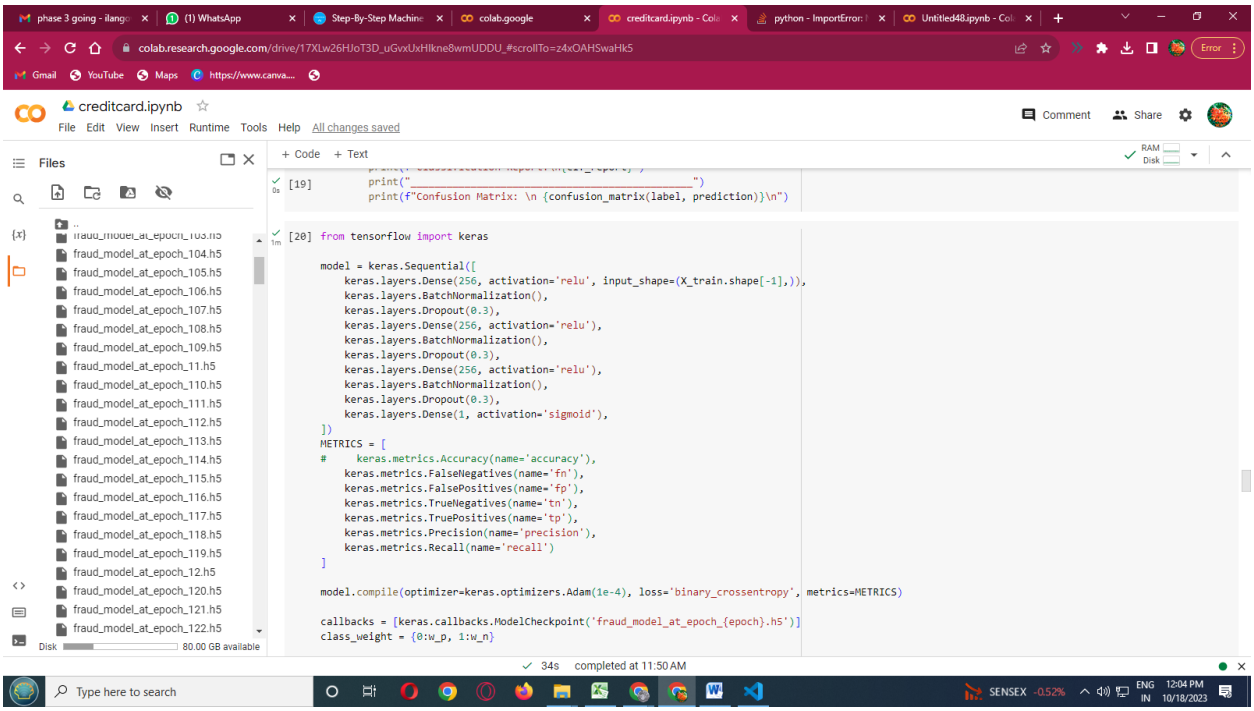



```
scalar = StandardScaler()

X = data.drop('Class', axis=1)
y = data.Class

X_train_v, X_test, y_train_v, y_test = train_test_split(X, y,
                                                        test_size=0.3, random_state=42)
X_train, X_validate, y_train, y_validate = train_test_split(X_train_v, y_train_v,
                                                            test_size=0.2, random_state=42)

X_train = scalar.fit_transform(X_train)
X_validate = scalar.transform(X_validate)
X_test = scalar.transform(X_test)

w_p = y_train.value_counts()[0] / len(y_train)
w_n = y_train.value_counts()[1] / len(y_train)

print(f"Fraudulant transaction weight: {w_n}")
print(f"Non-Fraudulant transaction weight: {w_p}")
```

```
Fraudulant transaction weight: 0.0007145409074669524
Non-Fraudulant transaction weight: 0.9992854590925331
```

```
[17] print(f"TRAINING: X_train: {X_train.shape}, y_train: {y_train.shape}\n{'_'*55}")
     print(f"VALIDATION: X_validate: {X_validate.shape}, y_validate: {y_validate.shape}\n{'_'*50}")
     print(f"TESTING: X_test: {X_test.shape}, y_test: {y_test.shape}")
```

```
TRAINING: X_train: (2799, 30), y_train: (2799,)
_______________________________________________________
VALIDATION: X_validate: (700, 30), y_validate: (700,)
__________________________________________________
```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[19] print("_____")
print(f"Confusion Matrix: \n {confusion_matrix(label, prediction)}\n")
[20] from tensorflow import keras
model = keras.Sequential([
keras.layers.Dense(256, activation='relu', input_shape=(X_train.shape[-1],)),
keras.layers.BatchNormalization(),
keras.layers.Dropout(0.3),
keras.layers.Dense(256, activation='relu'),
keras.layers.BatchNormalization(),
keras.layers.Dropout(0.3),
keras.layers.Dense(256, activation='relu'),
keras.layers.BatchNormalization(),
keras.layers.Dropout(0.3),
keras.layers.Dense(1, activation='sigmoid'),
])
METRICS = [
# keras.metrics.Accuracy(name='accuracy'),
keras.metrics.FalseNegatives(name='fn'),
keras.metrics.FalsePositives(name='fp'),
keras.metrics.TrueNegatives(name='tn'),
keras.metrics.TruePositives(name='tp'),
keras.metrics.Precision(name='precision'),
keras.metrics.Recall(name='recall')
]
model.compile(optimizer=keras.optimizers.Adam(1e-4), loss='binary_crossentropy', metrics=METRICS)
callbacks = [keras.callbacks.ModelCheckpoint('fraud_model_at_epoch_{epoch}.h5')]
class_weight = {0:w_p, 1:w_n}
fraud_model_at_epoch_104.h5
fraud_model_at_epoch_105.h5
fraud_model_at_epoch_106.h5
fraud_model_at_epoch_107.h5
fraud_model_at_epoch_108.h5
fraud_model_at_epoch_109.h5
fraud_model_at_epoch_11.h5
fraud_model_at_epoch_110.h5
fraud_model_at_epoch_111.h5
fraud_model_at_epoch_112.h5
fraud_model_at_epoch_113.h5
fraud_model_at_epoch_114.h5
fraud_model_at_epoch_115.h5
fraud_model_at_epoch_116.h5
fraud_model_at_epoch_117.h5
fraud_model_at_epoch_118.h5
fraud_model_at_epoch_119.h5
fraud_model_at_epoch_12.h5
fraud_model_at_epoch_120.h5
fraud_model_at_epoch_121.h5
fraud_model_at_epoch_122.h5
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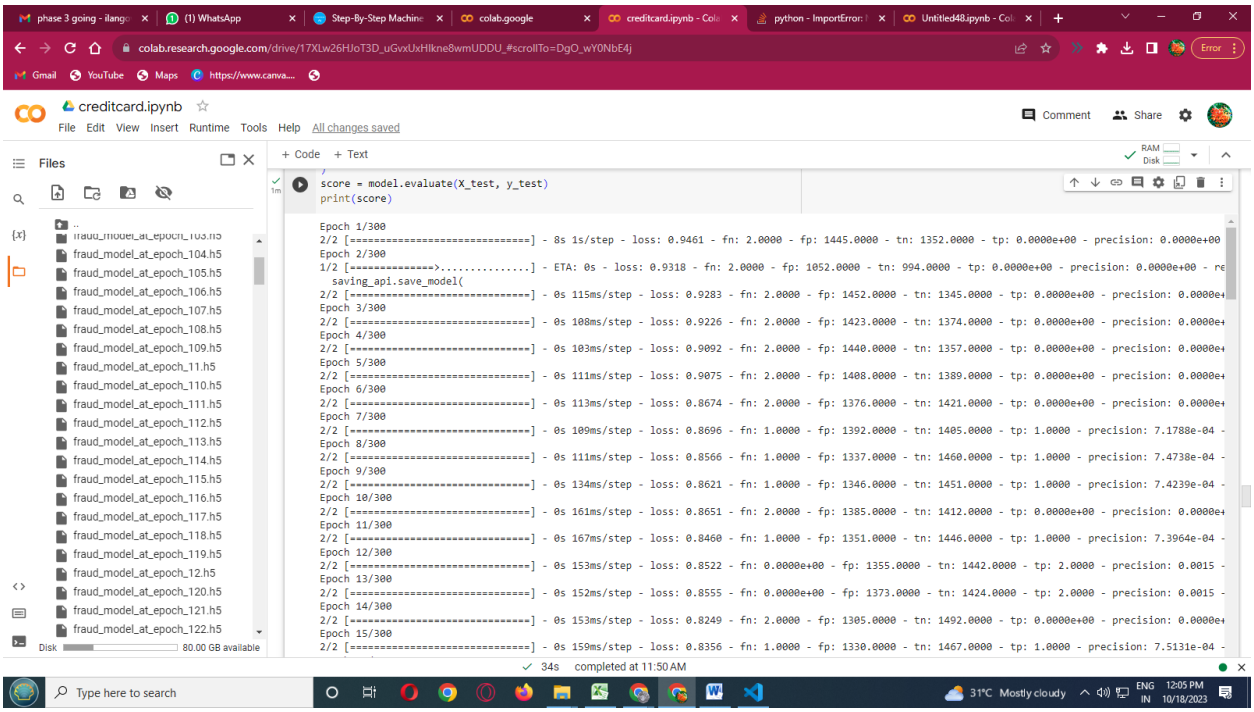
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score = model.evaluate(X_test, y_test)
print(score)
Epoch 1/300
2/2 [==========] - 8s 1s/step - loss: 0.9461 - fn: 2.0000 - fp: 1445.0000 - tn: 1352.0000 - tp: 0.0000e+00 - precision: 0.0000e+00
Epoch 2/300
1/2 [==========>.....] - ETA: 0s - loss: 0.9318 - fn: 2.0000 - fp: 1052.0000 - tn: 994.0000 - tp: 0.0000e+00 - precision: 0.0000e+00 - re
saving_api.save_model(
2/2 [==========] - 0s 115ms/step - loss: 0.9283 - fn: 2.0000 - fp: 1452.0000 - tn: 1345.0000 - tp: 0.0000e+00 - precision: 0.0000e+
Epoch 3/300
2/2 [==========] - 0s 108ms/step - loss: 0.9226 - fn: 2.0000 - fp: 1423.0000 - tn: 1374.0000 - tp: 0.0000e+00 - precision: 0.0000e+
Epoch 4/300
2/2 [==========] - 0s 103ms/step - loss: 0.9092 - fn: 2.0000 - fp: 1440.0000 - tn: 1357.0000 - tp: 0.0000e+00 - precision: 0.0000e+
Epoch 5/300
2/2 [==========] - 0s 111ms/step - loss: 0.9075 - fn: 2.0000 - fp: 1408.0000 - tn: 1389.0000 - tp: 0.0000e+00 - precision: 0.0000e+
Epoch 6/300
2/2 [==========] - 0s 113ms/step - loss: 0.8674 - fn: 2.0000 - fp: 1376.0000 - tn: 1421.0000 - tp: 0.0000e+00 - precision: 0.0000e+
Epoch 7/300
2/2 [==========] - 0s 109ms/step - loss: 0.8696 - fn: 1.0000 - fp: 1392.0000 - tn: 1405.0000 - tp: 1.0000 - precision: 7.1788e-04 -
Epoch 8/300
2/2 [==========] - 0s 111ms/step - loss: 0.8566 - fn: 1.0000 - fp: 1337.0000 - tn: 1460.0000 - tp: 1.0000 - precision: 7.4738e-04 -
Epoch 9/300
2/2 [==========] - 0s 134ms/step - loss: 0.8621 - fn: 1.0000 - fp: 1346.0000 - tn: 1451.0000 - tp: 1.0000 - precision: 7.4239e-04 -
Epoch 10/300
2/2 [==========] - 0s 161ms/step - loss: 0.8651 - fn: 2.0000 - fp: 1385.0000 - tn: 1412.0000 - tp: 0.0000e+00 - precision: 0.0000e+
Epoch 11/300
2/2 [==========] - 0s 167ms/step - loss: 0.8460 - fn: 1.0000 - fp: 1351.0000 - tn: 1446.0000 - tp: 1.0000 - precision: 7.3964e-04 -
Epoch 12/300
2/2 [==========] - 0s 153ms/step - loss: 0.8522 - fn: 0.0000e+00 - fp: 1355.0000 - tn: 1442.0000 - tp: 2.0000 - precision: 0.0015 -
Epoch 13/300
2/2 [==========] - 0s 152ms/step - loss: 0.8555 - fn: 0.0000e+00 - fp: 1373.0000 - tn: 1424.0000 - tp: 2.0000 - precision: 0.0015 -
Epoch 14/300
2/2 [==========] - 0s 153ms/step - loss: 0.8249 - fn: 2.0000 - fp: 1305.0000 - tn: 1492.0000 - tp: 0.0000e+00 - precision: 0.0000e+
Epoch 15/300
2/2 [==========] - 0s 159ms/step - loss: 0.8356 - fn: 1.0000 - fp: 1330.0000 - tn: 1467.0000 - tp: 1.0000 - precision: 7.5131e-04 -
fraud_model_at_epoch_104.h5
fraud_model_at_epoch_105.h5
fraud_model_at_epoch_106.h5
fraud_model_at_epoch_107.h5
fraud_model_at_epoch_108.h5
fraud_model_at_epoch_109.h5
fraud_model_at_epoch_11.h5
fraud_model_at_epoch_110.h5
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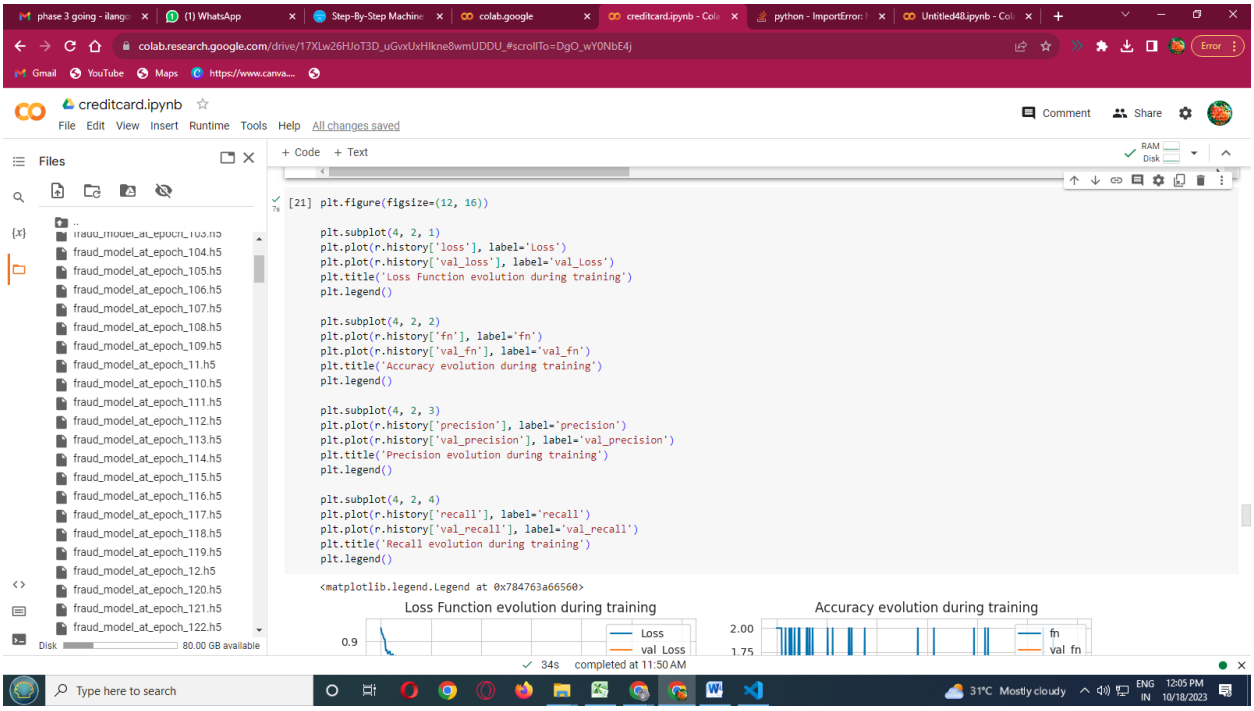
fraud_model_at_epoch_112.h5
fraud_model_at_epoch_113.h5
fraud_model_at_epoch_114.h5
fraud_model_at_epoch_115.h5
fraud_model_at_epoch_116.h5
fraud_model_at_epoch_117.h5
fraud_model_at_epoch_118.h5
fraud_model_at_epoch_119.h5
fraud_model_at_epoch_12.h5
fraud_model_at_epoch_120.h5
fraud_model_at_epoch_121.h5
fraud_model_at_epoch_122.h5
Disk 80.00 GB available
34s completed at 11:50 AM
Type here to search
31°C Mostly cloudy
ENG IN 12:05 PM 10/18/2023


creditcard.ipynb
File Edit View Insert Runtime Tools Help All changes saved
Comment
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[21] plt.figure(figsize=(12, 16))
plt.subplot(4, 2, 1)
plt.plot(r.history['loss'], label='Loss')
plt.plot(r.history['val_loss'], label='val_Loss')
plt.title('Loss Function evolution during training')
plt.legend()
plt.subplot(4, 2, 2)
plt.plot(r.history['fn'], label='fn')
plt.plot(r.history['val_fn'], label='val_fn')
plt.title('Accuracy evolution during training')
plt.legend()
plt.subplot(4, 2, 3)
plt.plot(r.history['precision'], label='precision')
plt.plot(r.history['val_precision'], label='val_precision')
plt.title('Precision evolution during training')
plt.legend()
plt.subplot(4, 2, 4)
plt.plot(r.history['recall'], label='recall')
plt.plot(r.history['val_recall'], label='val_recall')
plt.title('Recall evolution during training')
plt.legend()
<matplotlib.legend.Legend at 0x784763a66560>
Loss Function evolution during training
Accuracy evolution during training
Loss
val_Loss
fn
val_fn
34s completed at 11:50 AM
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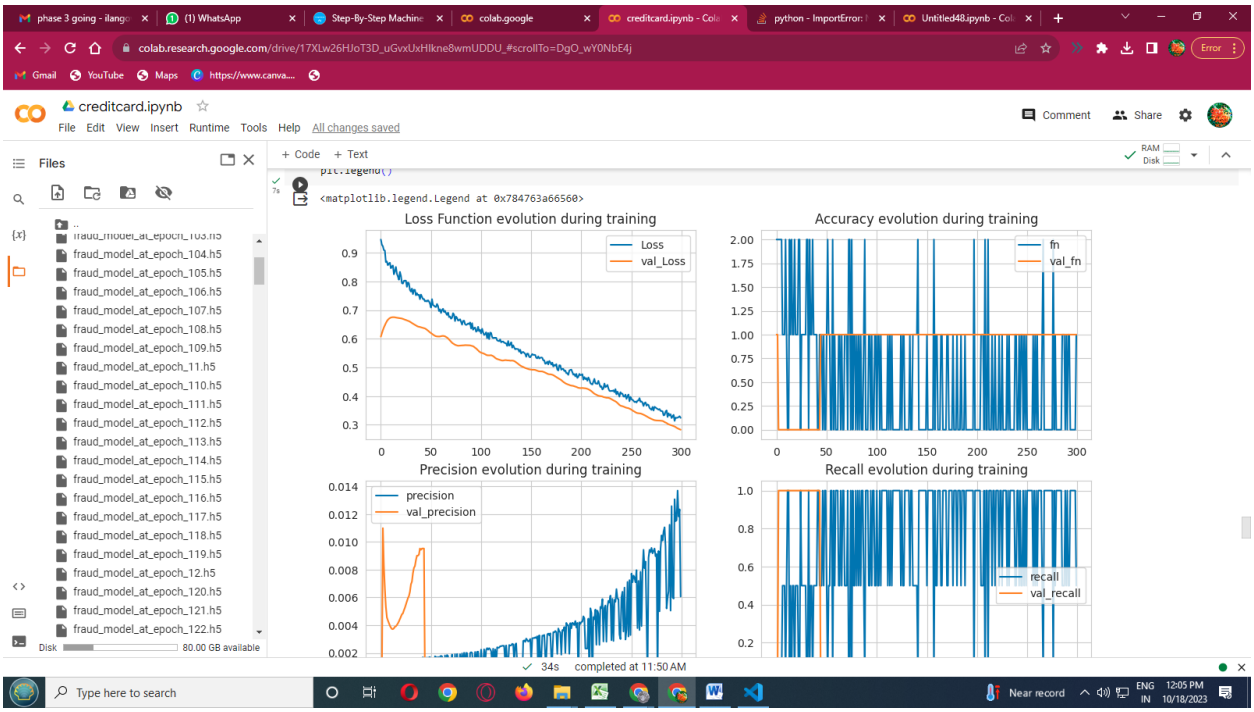
31°C Mostly cloudy
ENG IN 12:05 PM 10/18/2023


creditcard.ipynb
File Edit View Insert Runtime Tools Help All changes saved
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<matplotlib.legend.Legend at 0x784763a66560>
Loss Function evolution during training
Accuracy evolution during training
Loss
val_Loss
fn
val_fn
Precision evolution during training
Recall evolution during training
precision
val_precision
recall
val_recall
34s completed at 11:50 AM
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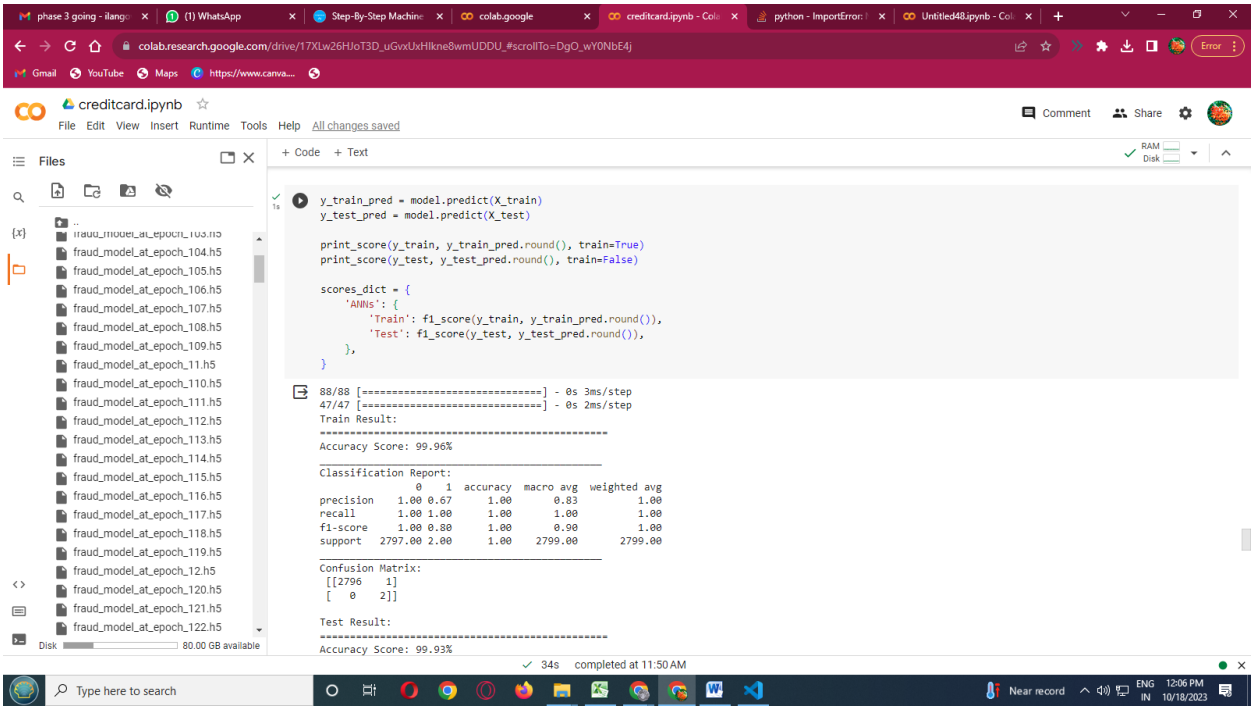
Near record
ENG IN 12:05 PM 10/18/2023



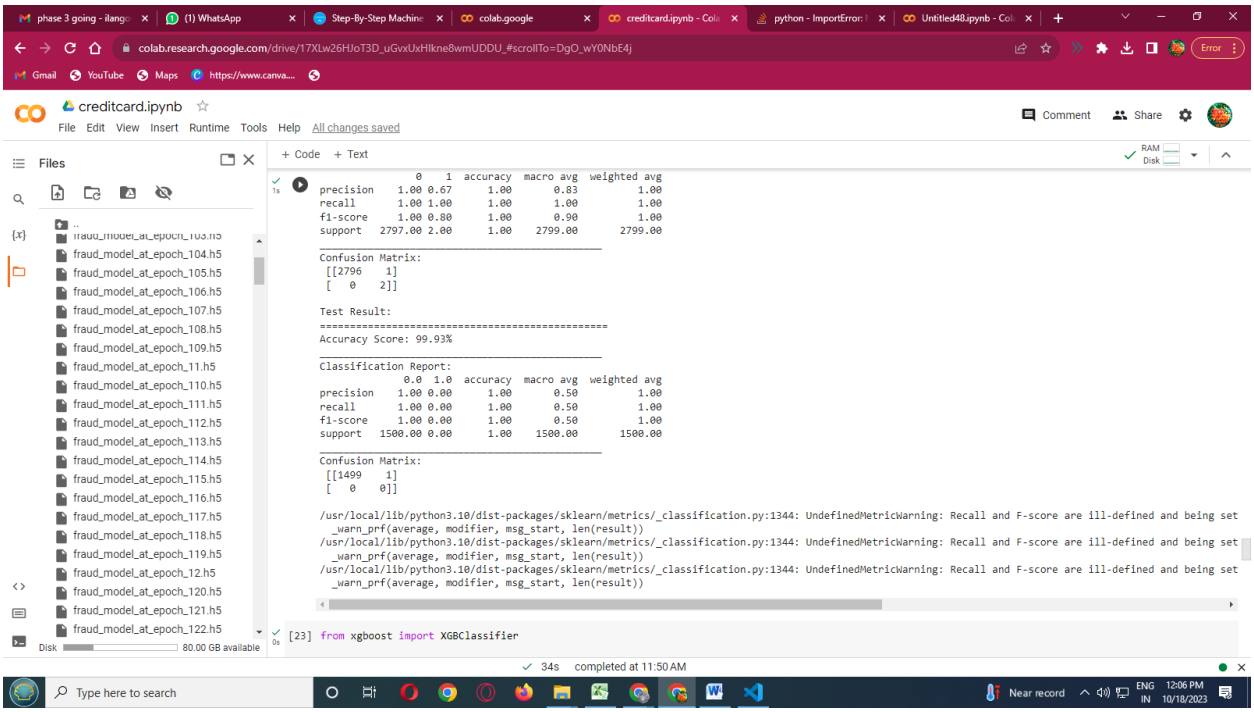
```
y_train_pred = model.predict(X_train)
y_test_pred = model.predict(X_test)

print_score(y_train, y_train_pred.round(), train=True)
print_score(y_test, y_test_pred.round(), train=False)

scores_dict = {
    'ANNs': {
        'Train': f1_score(y_train, y_train_pred.round()),
        'Test': f1_score(y_test, y_test_pred.round()),
    },
}
```

```
88/88 [==============================] - 0s 3ms/step
47/47 [==============================] - 0s 2ms/step
Train Result:
================================================
Accuracy Score: 99.96%
________________________________________________
Classification Report:
                    0    1  accuracy  macro avg  weighted avg
precision        1.00 0.67      1.00       0.83          1.00
recall           1.00 1.00      1.00       1.00          1.00
f1-score         1.00 0.80      1.00       0.90          1.00
support       2797.00 2.00      1.00    2799.00       2799.00
________________________________________________
Confusion Matrix:
 [[2796    1]
 [   0    2]]

Test Result:
================================================
Accuracy Score: 99.93%
```

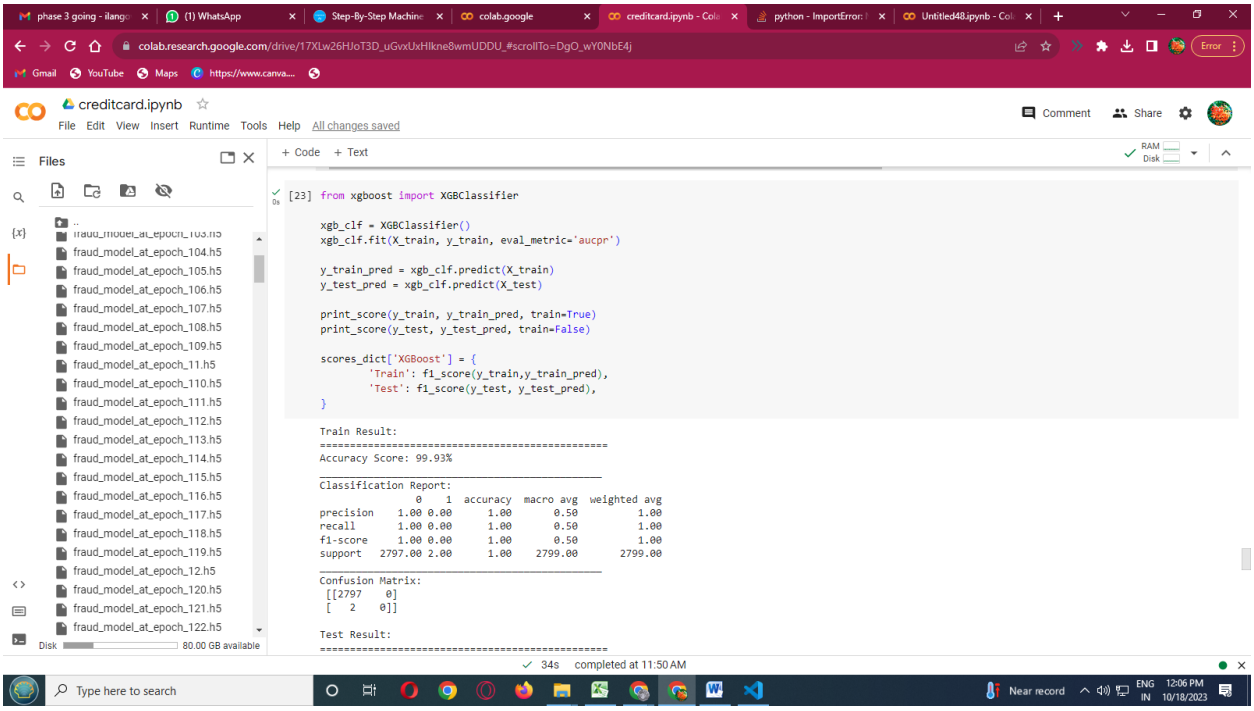


```
                    0    1  accuracy  macro avg  weighted avg
precision        1.00 0.67      1.00       0.83          1.00
recall           1.00 1.00      1.00       1.00          1.00
f1-score         1.00 0.80      1.00       0.90          1.00
support       2797.00 2.00      1.00    2799.00       2799.00
________________________________________________
Confusion Matrix:
 [[2796    1]
 [   0    2]]

Test Result:
================================================
Accuracy Score: 99.93%
________________________________________________
Classification Report:
                   0.0  1.0  accuracy  macro avg  weighted avg
precision        1.00 0.00      1.00       0.50          1.00
recall           1.00 0.00      1.00       0.50          1.00
f1-score         1.00 0.00      1.00       0.50          1.00
support       1500.00 0.00      1.00    1500.00       1500.00
________________________________________________
Confusion Matrix:
 [[1499    1]
 [   0    0]]

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Recall and F-score are ill-defined and being set
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Recall and F-score are ill-defined and being set
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Recall and F-score are ill-defined and being set
  _warn_prf(average, modifier, msg_start, len(result))
```

```
from xgboost import XGBClassifier
```


creditcard.ipynb
File Edit View Insert Runtime Tools Help All changes saved
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[23] from xgboost import XGBClassifier
xgb_clf = XGBClassifier()
xgb_clf.fit(X_train, y_train, eval_metric='aucpr')
y_train_pred = xgb_clf.predict(X_train)
y_test_pred = xgb_clf.predict(X_test)
print_score(y_train, y_train_pred, train=True)
print_score(y_test, y_test_pred, train=False)
scores_dict['XGBoost'] = {
'Train': f1_score(y_train,y_train_pred),
'Test': f1_score(y_test, y_test_pred),
}
Train Result:
Accuracy Score: 99.93%
Classification Report:
0 1 accuracy macro avg weighted avg
precision 1.00 0.00 1.00 0.50 1.00
recall 1.00 0.00 1.00 0.50 1.00
f1-score 1.00 0.00 1.00 0.50 1.00
support 2797.00 2.00 1.00 2799.00 2799.00
Confusion Matrix:
[[2797 0]
[2 0]]
Test Result:
34s completed at 11:50 AM
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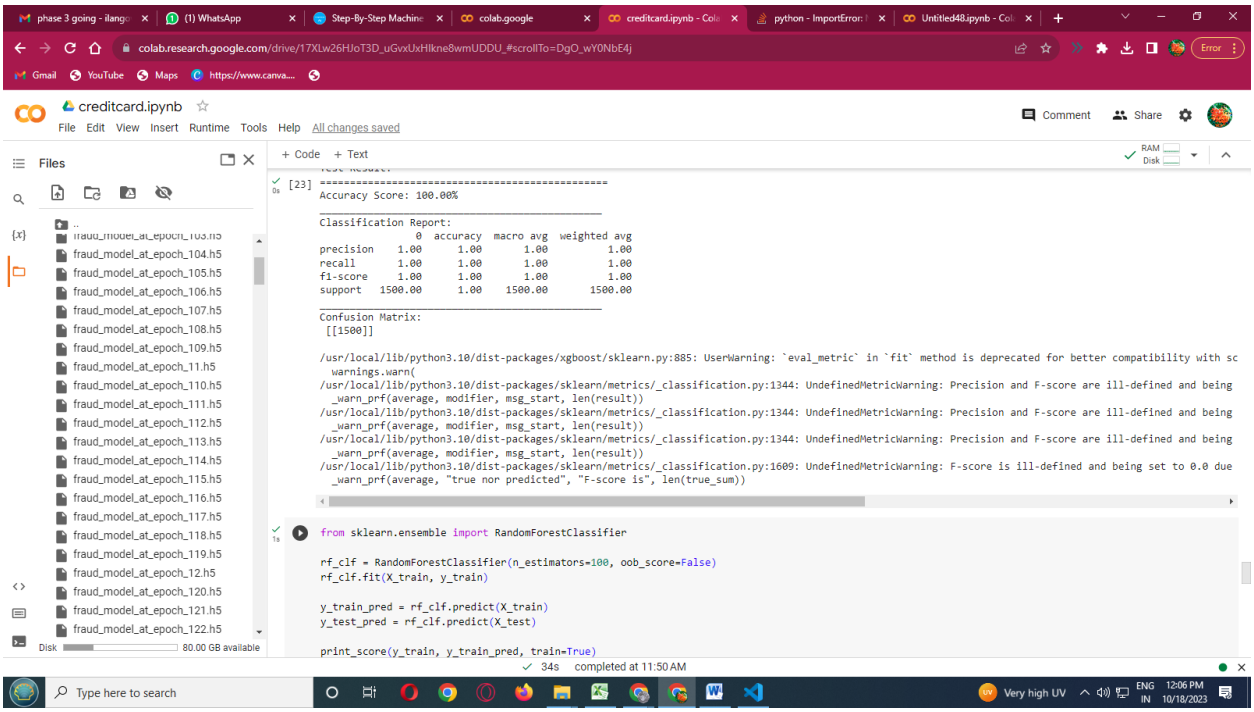
Near record
ENG IN 12:06 PM 10/18/2023


creditcard.ipynb
File Edit View Insert Runtime Tools Help All changes saved
Comment
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[23] Accuracy Score: 100.00%
Classification Report:
0 accuracy macro avg weighted avg
precision 1.00 1.00 1.00 1.00
recall 1.00 1.00 1.00 1.00
f1-score 1.00 1.00 1.00 1.00
support 1500.00 1.00 1500.00 1500.00
Confusion Matrix:
[[1500]]
/usr/local/lib/python3.10/dist-packages/xgboost/sklearn.py:885: UserWarning: `eval_metric` in `fit` method is deprecated for better compatibility with sc
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1609: UndefinedMetricWarning: F-score is ill-defined and being set to 0.0 due
_warn_prf(average, "true nor predicted", "F-score is", len(true_sum))
from sklearn.ensemble import RandomForestClassifier
rf_clf = RandomForestClassifier(n_estimators=100, oob_score=False)
rf_clf.fit(X_train, y_train)
y_train_pred = rf_clf.predict(X_train)
y_test_pred = rf_clf.predict(X_test)
print_score(y_train, y_train_pred, train=True)
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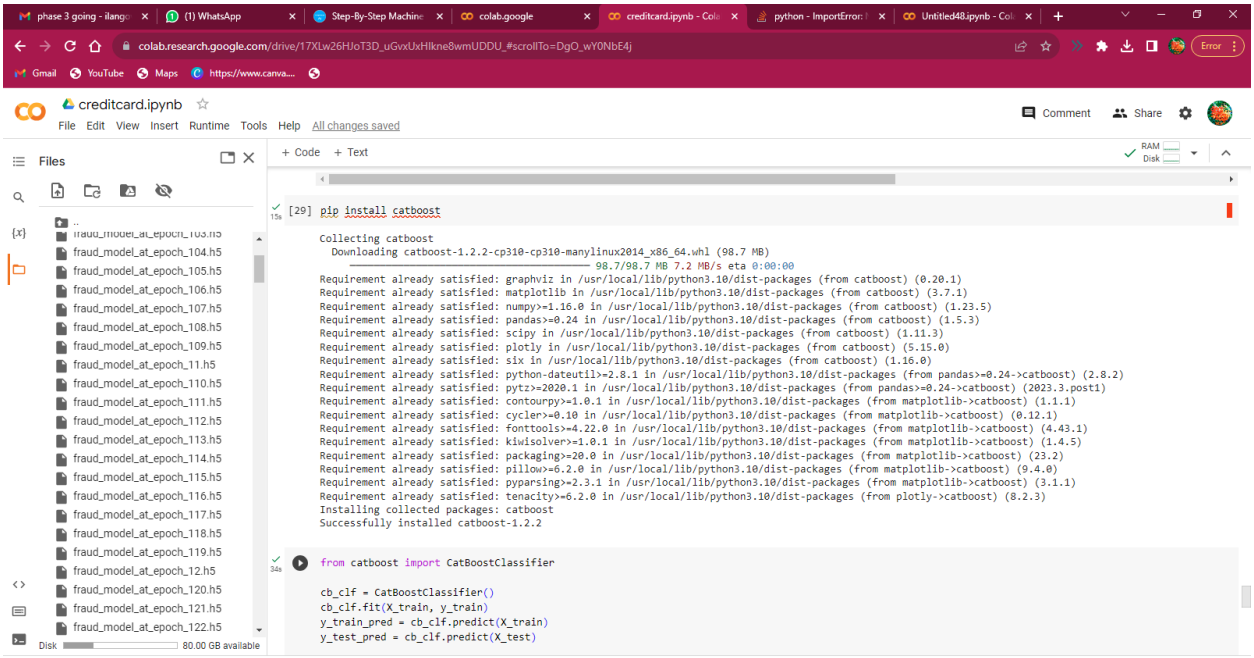
Very high UV
ENG IN 12:06 PM 10/18/2023


creditcard.ipynb
File Edit View Insert Runtime Tools Help All changes saved
Comment
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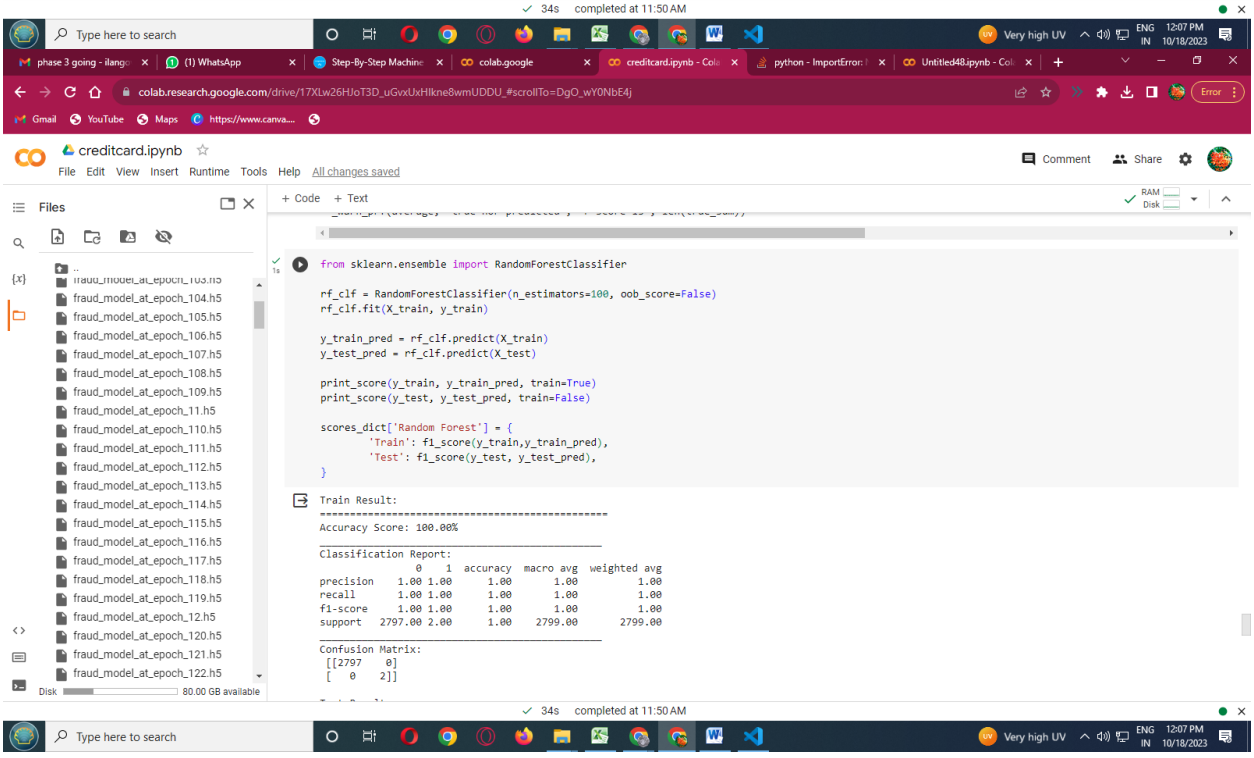
[29] pip install catboost
Collecting catboost
Downloading catboost-1.2.2-cp310-cp310-manylinux2014_x86_64.whl (98.7 MB)
98.7/98.7 MB 7.2 MB/s eta 0:00:00
Requirement already satisfied: graphviz in /usr/local/lib/python3.10/dist-packages (from catboost) (0.20.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from catboost) (3.7.1)
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.10/dist-packages (from catboost) (1.23.5)
Requirement already satisfied: pandas>=0.24 in /usr/local/lib/python3.10/dist-packages (from catboost) (1.5.3)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from catboost) (1.11.3)
Requirement already satisfied: plotly in /usr/local/lib/python3.10/dist-packages (from catboost) (5.15.0)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from catboost) (1.16.0)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.24->catboost) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.24->catboost) (2023.3.post1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (1.1.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (4.43.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (1.4.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (23.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (3.1.1)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from plotly->catboost) (8.2.3)
Installing collected packages: catboost
Successfully installed catboost-1.2.2
from catboost import CatBoostClassifier
cb_clf = CatBoostClassifier()
cb_clf.fit(X_train, y_train)
y_train_pred = cb_clf.predict(X_train)
y_test_pred = cb_clf.predict(X_test)
34s completed at 11:50 AM


creditcard.ipynb
File Edit View Insert Runtime Tools Help All changes saved
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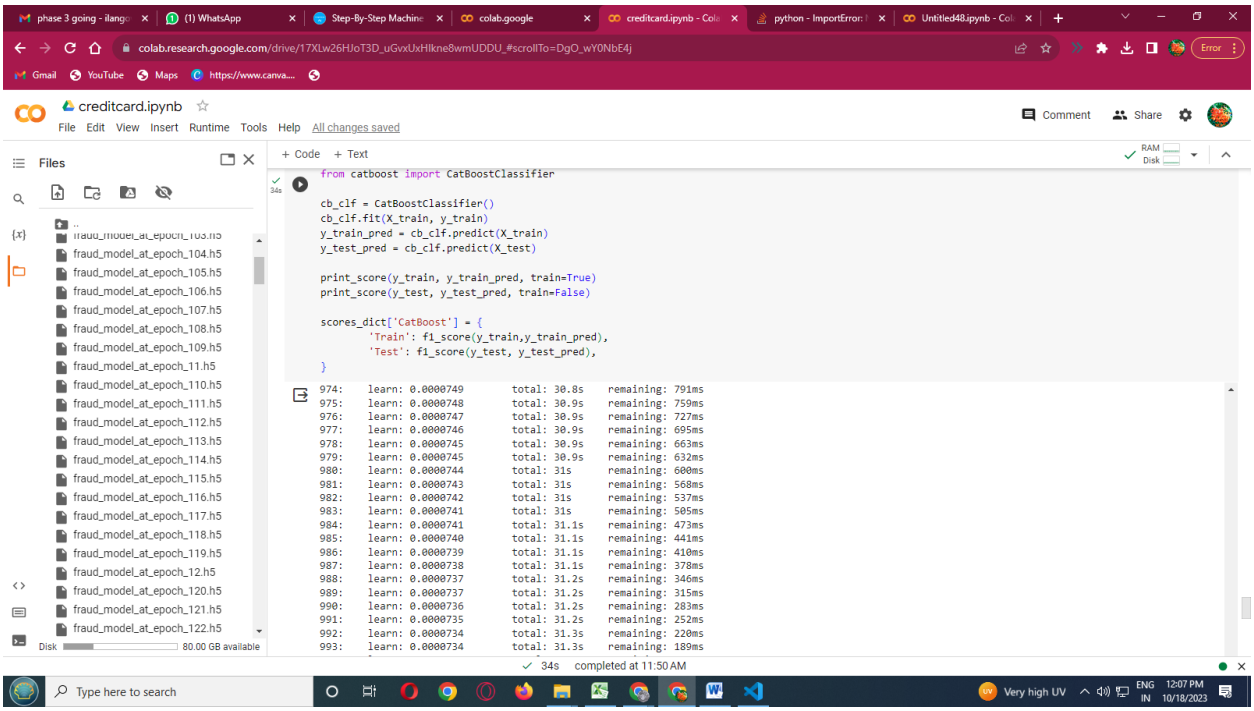
from sklearn.ensemble import RandomForestClassifier
rf_clf = RandomForestClassifier(n_estimators=100, oob_score=False)
rf_clf.fit(X_train, y_train)
y_train_pred = rf_clf.predict(X_train)
y_test_pred = rf_clf.predict(X_test)
print_score(y_train, y_train_pred, train=True)
print_score(y_test, y_test_pred, train=False)
scores_dict['Random Forest'] = {
'Train': f1_score(y_train,y_train_pred),
'Test': f1_score(y_test, y_test_pred),
}
Train Result:
Accuracy Score: 100.00%
Classification Report:
0 1 accuracy macro avg weighted avg
precision 1.00 1.00 1.00 1.00 1.00
recall 1.00 1.00 1.00 1.00 1.00
f1-score 1.00 1.00 1.00 1.00 1.00
support 2797.00 2.00 1.00 2799.00 2799.00
Confusion Matrix:
[[2797 0]
[0 2]]
34s completed at 11:50 AM


creditcard.ipynb
File Edit View Insert Runtime Tools Help All changes saved
Comment
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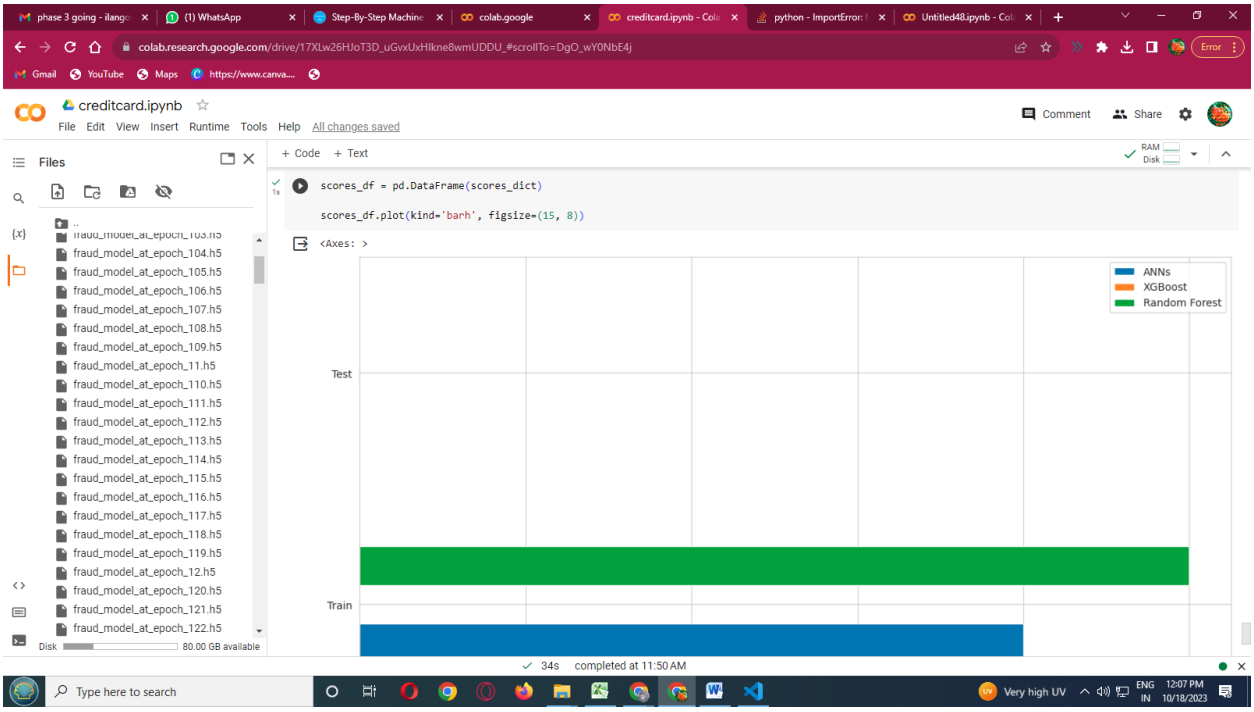
from catboost import CatBoostClassifier
cb_clf = CatBoostClassifier()
cb_clf.fit(X_train, y_train)
y_train_pred = cb_clf.predict(X_train)
y_test_pred = cb_clf.predict(X_test)
print_score(y_train, y_train_pred, train=True)
print_score(y_test, y_test_pred, train=False)
scores_dict['CatBoost'] = {
'Train': f1_score(y_train,y_train_pred),
'Test': f1_score(y_test, y_test_pred),
}
974: learn: 0.0000749 total: 30.8s remaining: 791ms
975: learn: 0.0000748 total: 30.9s remaining: 759ms
976: learn: 0.0000747 total: 30.9s remaining: 727ms
977: learn: 0.0000746 total: 30.9s remaining: 695ms
978: learn: 0.0000745 total: 30.9s remaining: 663ms
979: learn: 0.0000745 total: 30.9s remaining: 632ms
980: learn: 0.0000744 total: 31s remaining: 600ms
981: learn: 0.0000743 total: 31s remaining: 568ms
982: learn: 0.0000742 total: 31s remaining: 537ms
983: learn: 0.0000741 total: 31s remaining: 505ms
984: learn: 0.0000741 total: 31.1s remaining: 473ms
985: learn: 0.0000740 total: 31.1s remaining: 441ms
986: learn: 0.0000739 total: 31.1s remaining: 410ms
987: learn: 0.0000738 total: 31.1s remaining: 378ms
988: learn: 0.0000737 total: 31.2s remaining: 346ms
989: learn: 0.0000737 total: 31.2s remaining: 315ms
990: learn: 0.0000736 total: 31.2s remaining: 283ms
991: learn: 0.0000735 total: 31.2s remaining: 252ms
992: learn: 0.0000734 total: 31.3s remaining: 220ms
993: learn: 0.0000734 total: 31.3s remaining: 189ms
34s completed at 11:50 AM


creditcard.ipynb
File Edit View Insert Runtime Tools Help All changes saved
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scores_df = pd.DataFrame(scores_dict)
scores_df.plot(kind='barh', figsize=(15, 8))
<Axes: >
ANNs
XGBoost
Random Forest
Test
Train
34s completed at 11:50 AM

Conclusion

In conclusion, preprocessing data before applying it to a machine learning algorithm is a crucial step in the ML workflow. It helps to improve the accuracy, reduce the time and resources required to train the model, prevent overfitting, and improve the interpretability of the model.

The above code example demonstrates how to preprocess data using the popular Python library, Pandas, but there are many other libraries available for preprocessing data, such as NumPy and Scikit-learn, that can be used depending on the specific needs of your project.