ITCS_3156_Final_Project_AndrewGreen

May 6, 2025

1 ITCS-3156 Final Project Spring 2025

1.1 Name: Andrew Green

1.2 Project Name: Credit Card Fraud Detection using Machine Learning

[1]:
```python
# Import the necessary modules

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from collections import Counter
import itertools

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, precision_score, confusion_matrix,␣
↪recall_score, f1_score
```

1.3 Data Loading

[2]:
```python
# Load the csv file
# dataset are downloaded from : https://www.kaggle.com/datasets/mlg-ulb/
↪creditcardfraud

credit_df = pd.read_csv("creditcard.csv")
credit_df.head()
```

[2]:
```
   Time        V1        V2        V3        V4        V5        V6        V7  \
0   0.0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
1   0.0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
2   1.0 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
3   1.0 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
4   2.0 -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]
```

1.4 Exploratory Data Analysis

[3]:
```python
credit_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
```

```
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

[4]:
```
# Check for null values

credit_df.isnull().values.any()
```

[4]:
```
np.False_
```

[5]:
```
credit_df["Amount"].describe()
```

[5]:
```
count    284807.000000
mean         88.349619
std         250.120109
min           0.000000
25%           5.600000
50%          22.000000
75%          77.165000
max       25691.160000
Name: Amount, dtype: float64
```

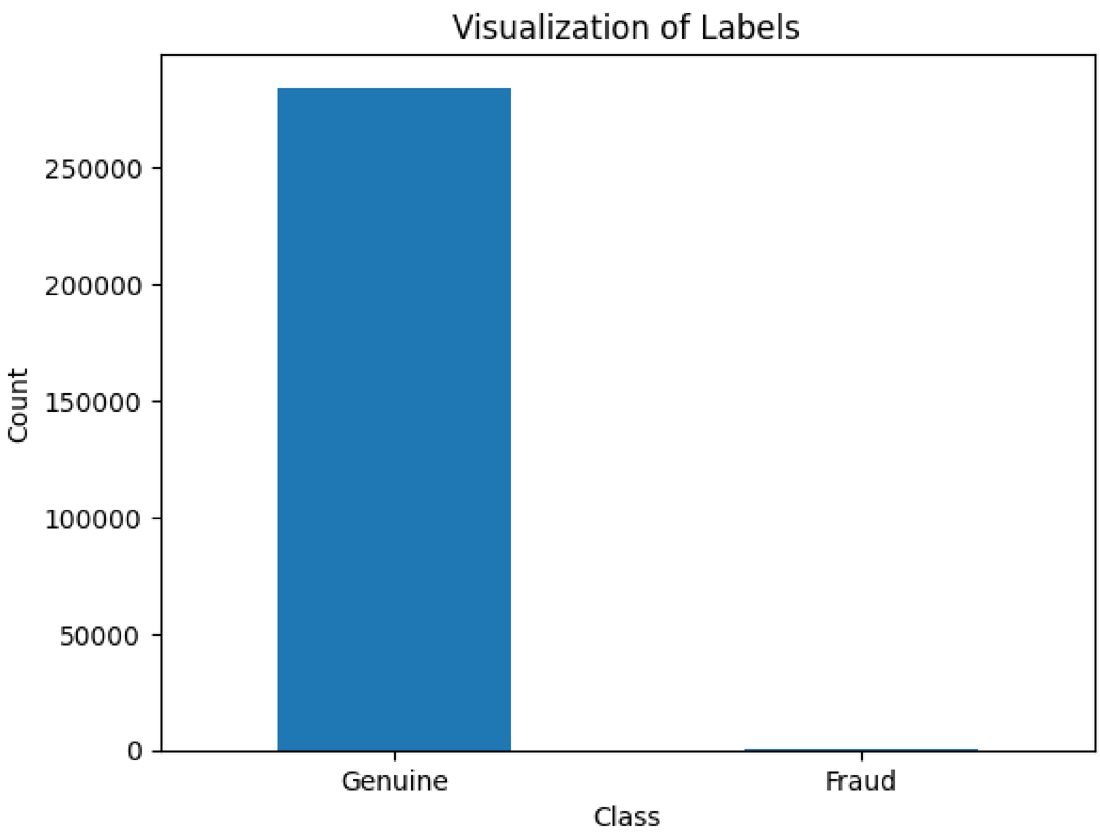
[6]:
```
non_fraud = len(credit_df[credit_df.Class == 0])
fraud = len(credit_df[credit_df.Class == 1])
fraud_percent = (fraud / (fraud + non_fraud)) * 100

print("Number of Genuine transactions: ", non_fraud)
print("Number of Fraud transactions: ", fraud)
print("Percentage of Fraud transactions: {:.4f}".format(fraud_percent))
```

```
Number of Genuine transactions:  284315
Number of Fraud transactions:  492
Percentage of Fraud transactions: 0.1727
```

The Percentage of Fraud transactions is only 0.17%. We can see how imbalance the data is !

[7]:
```
# Visualize the "Labels" column in our dataset

labels = ["Genuine", "Fraud"]
count_classes = credit_df.value_counts(credit_df['Class'], sort= True)
count_classes.plot(kind = "bar", rot = 0)
plt.title("Visualization of Labels")
```

```
plt.ylabel("Count")
plt.xticks(range(2), labels)
plt.show()
```



1.5 Data Preprocessing

[8]:
```
# Perform Scaling on Amount
df2 = credit_df.copy()

scaler = StandardScaler()
df2["NormalizedAmount"] = scaler.fit_transform(df2["Amount"].values.reshape(-1,␣
↪1))
df2.drop(["Amount", "Time"], inplace= True, axis= 1)

y = df2["Class"]
X = df2.drop(["Class"], axis= 1)
```

[9]:
```
y.head()
```

[9]:
```
0    0
1    0
2    0
3    0
4    0
Name: Class, dtype: int64
```

[10]:
```
# Split the data
#(train_X, test_X, train_Y, test_Y) = train_test_split(X, Y, test_size= 0.3,␣
↪random_state= 42)
X_trn, X_tst, y_trn, y_tst = train_test_split(X, y, train_size=.8,␣
↪random_state=42)
X_trn, X_vld, y_trn, y_vld = train_test_split(X_trn, y_trn, train_size=.8,␣
↪random_state=42)

print("Shape of X_trn: ", X_trn.shape)
print("Shape of y_trn: ", y_trn.shape)
print("Shape of X_vld: ", X_vld.shape)
print("Shape of y_vld: ", y_vld.shape)
print("Shape of X_tst: ", X_tst.shape)
print("Shape of y_tst: ", y_tst.shape)
```

```
Shape of X_trn:  (182276, 29)
Shape of y_trn:  (182276,)
Shape of X_vld:  (45569, 29)
Shape of y_vld:  (45569,)
Shape of X_tst:  (56962, 29)
Shape of y_tst:  (56962,)
```

1.5.1 Helper function

[11]:
```
# The below function is directly taken from the scikit-learn website to plot␣
↪the confusion matrix

def plot_confusion_matrix(cm, classes, normalize=False, title='Confusion␣
↪Matrix', cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')
```

```
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=0)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt), horizontalalignment="center",␣
 ↪color="white" if cm[i, j] > thresh else "black")

    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()

# The below function prints the following necesary metrics

def metrics(actuals, predictions):
    accuracy = accuracy_score(actuals, predictions)
    precision = precision_score(actuals, predictions)
    recall = recall_score(actuals, predictions)
    f1score = f1_score(actuals, predictions)
    print("Accuracy: {:.5f}".format(accuracy))
    print("Precision: {:.5f}".format(precision))
    print("Recall: {:.5f}".format(recall))
    print("F1-score: {:.5f}".format(f1score))

    return (accuracy, precision, recall, f1score)
```

1.6 Decision Tree Classifier

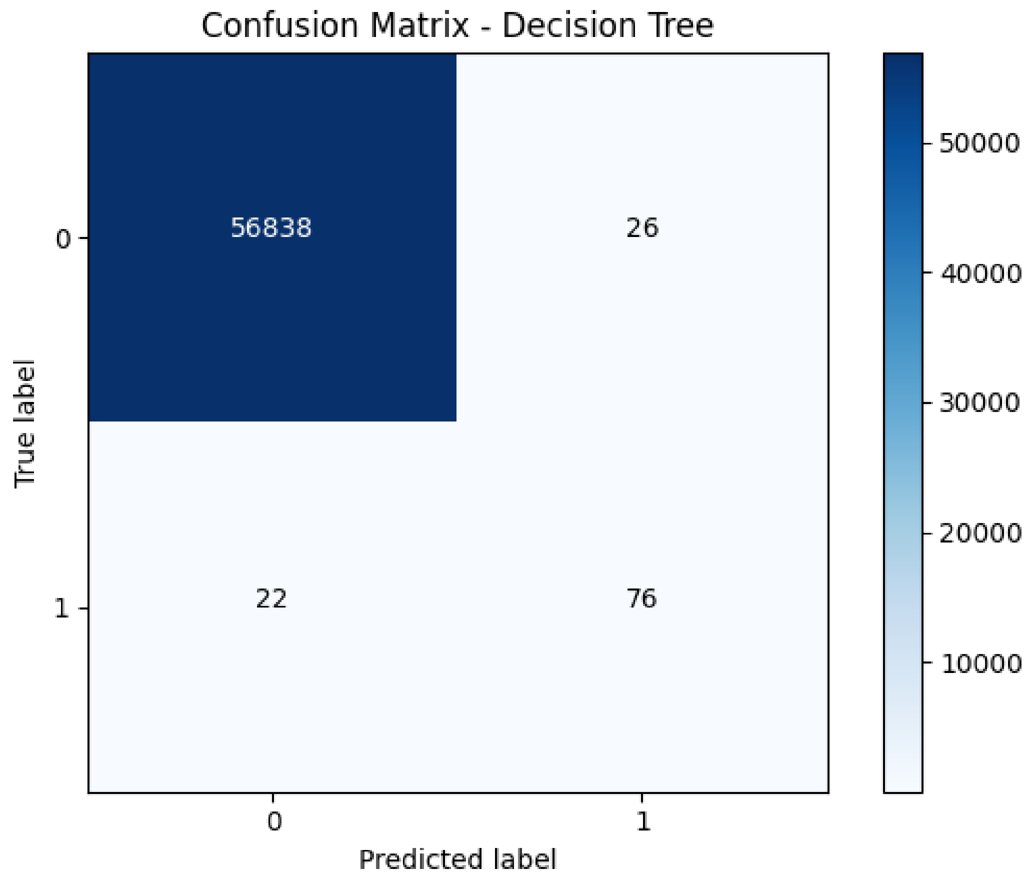
[12]:
```
# Decision Tree Classifier
decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_trn, y_trn)

predictions_dt = decision_tree.predict(X_tst)
decision_tree_score = decision_tree.score(X_tst, y_tst) * 100
```

[13]:
```
# Plot confusion matrix for Decision Trees
confusion_matrix_dt = confusion_matrix(y_tst, predictions_dt.round())
print("Confusion Matrix - Decision Tree")
print(confusion_matrix_dt)
```

```
Confusion Matrix - Decision Tree
[[56838    26]
 [   22    76]]
```

[14]:
```
plot_confusion_matrix(confusion_matrix_dt, classes=[0, 1], title= "Confusion␣
↪Matrix - Decision Tree")
```

```
Confusion matrix, without normalization
```



[15]:
```
print("Evaluation of Decision Tree Model")
print()
metrics_dt = metrics(y_tst, predictions_dt.round())
```

```
Evaluation of Decision Tree Model

Accuracy: 0.99916
Precision: 0.74510
Recall: 0.77551
F1-score: 0.76000
```

1.7 Neural Network Classifier

[16]:
```
import keras
from keras import layers
```

1.7.1 Neural Network Creation

[17]:
```
model_kernel = keras.regularizers.l2(0.01)
layer_unit = 128
input_shape = (29,)

model = keras.models.Sequential([
    keras.Input(shape=input_shape),
    layers.Flatten(),
    layers.Dense(layer_unit, activation='relu',␣
 ↪kernel_regularizer=model_kernel),
    layers.Dense(layer_unit, activation='relu',␣
 ↪kernel_regularizer=model_kernel),
    layers.Dropout(0.2),
    layers.Dense(1, activation='sigmoid')
])

model.summary()
```

```
Model: "sequential"


 Layer (type)                         Output Shape                        ␣
↪Param #

 flatten (Flatten)                    (None, 29)                          ␣
↪   0

 dense (Dense)                        (None, 128)                         ␣
↪3,840

 dense_1 (Dense)                      (None, 128)                         ␣
↪16,512

 dropout (Dropout)                    (None, 128)                         ␣
↪   0

 dense_2 (Dense)                      (None, 1)                           ␣
↪129


 Total params: 20,481 (80.00 KB)
```

```
Trainable params: 20,481 (80.00 KB)

Non-trainable params: 0 (0.00 B)
```

1.7.2 Model compile

[18]:
```python
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

1.7.3 Train the model

[19]:
```python
# Train the model
history = model.fit(X_trn, y_trn, epochs=20)
```

```
Epoch 1/20
5697/5697            9s 1ms/step -
accuracy: 0.9981 - loss: 0.1474
Epoch 2/20
5697/5697            8s 1ms/step -
accuracy: 0.9991 - loss: 0.0074
Epoch 3/20
5697/5697            8s 1ms/step -
accuracy: 0.9992 - loss: 0.0063
Epoch 4/20
5697/5697            8s 1ms/step -
accuracy: 0.9992 - loss: 0.0059
Epoch 5/20
5697/5697            8s 1ms/step -
accuracy: 0.9992 - loss: 0.0055
Epoch 6/20
5697/5697            8s 1ms/step -
accuracy: 0.9992 - loss: 0.0054
Epoch 7/20
5697/5697            8s 1ms/step -
accuracy: 0.9992 - loss: 0.0056
Epoch 8/20
5697/5697            8s 1ms/step -
accuracy: 0.9991 - loss: 0.0057
Epoch 9/20
5697/5697            8s 1ms/step -
accuracy: 0.9993 - loss: 0.0051
Epoch 10/20
5697/5697            8s 1ms/step -
accuracy: 0.9992 - loss: 0.0050
```

```
Epoch 11/20
5697/5697            8s 1ms/step -
accuracy: 0.9991 - loss: 0.0056
Epoch 12/20
5697/5697            8s 1ms/step -
accuracy: 0.9992 - loss: 0.0052
Epoch 13/20
5697/5697            8s 1ms/step -
accuracy: 0.9991 - loss: 0.0054
Epoch 14/20
5697/5697            8s 1ms/step -
accuracy: 0.9993 - loss: 0.0048
Epoch 15/20
5697/5697            8s 1ms/step -
accuracy: 0.9992 - loss: 0.0053
Epoch 16/20
5697/5697            8s 1ms/step -
accuracy: 0.9993 - loss: 0.0045
Epoch 17/20
5697/5697            8s 1ms/step -
accuracy: 0.9992 - loss: 0.0050
Epoch 18/20
5697/5697            8s 1ms/step -
accuracy: 0.9993 - loss: 0.0043
Epoch 19/20
5697/5697            8s 1ms/step -
accuracy: 0.9992 - loss: 0.0054
Epoch 20/20
5697/5697            8s 1ms/step -
accuracy: 0.9993 - loss: 0.0047
```

[20]:
```
model.predict(X_tst)
```

```
1781/1781            1s 627us/step
```

[20]:
```
array([[7.6830745e-01],
       [2.7530853e-04],
       [3.8009480e-04],
       …,
       [3.7469860e-04],
       [2.7530853e-04],
       [4.9429457e-04]], dtype=float32)
```

1.7.4 Model Evaluate

[21]:
```
loss, accuracy = model.evaluate(X_tst, y_tst, verbose=2)
print('Test accuracy:', accuracy)
```

```
1781/1781 - 2s - 1ms/step - accuracy: 0.9992 - loss: 0.0045
```

```
Test accuracy: 0.9991924166679382
```

1.8 Oversampling for imbalanced data

As mentioned above, we can clearly observe the imbalance on our credit dataset. When dataset is imbalanced, the model learns to favor the majority class, leading to a high accuracy score that can be misleading. This bias can result in the model failing to accurately identify or predict instances of the minority class, even if it's crucial for the overall purpose of the mode.

The consequences of a biased model can be significant, particularly in areas where accuracy and reliability are paramount. For example, in fraud detection, a model that favors detecting non-fraudulent transactions might miss actual fraudulent activities, leading to financial losses. In medical diagnosis, a biased model could misclassify a rare disease, potentially leading to delayed or incorrect treatment.

The datasaet imbalance issue can be mitigated by various techniques, incuding Resampling, Class Weighting, Algorithm Selection and Adjusting Thresholding.

In this project, we will test the Resampling technique by oversampling the minority class (creating synthetic data) to balance the dataset.

[22]:
```
#from imblearn.over_sampling import SMOTE
from imblearn.over_sampling import RandomOverSampler

ros = RandomOverSampler(sampling_strategy='auto',random_state=0)

X_resampled, y_resampled = ros.fit_resample(X, y)

print("Resampled shape of X: ", X_resampled.shape)
print("Resampled shape of y: ", y_resampled.shape)

value_counts = Counter(y_resampled)
print(value_counts)
```

```
Resampled shape of X:  (568630, 29)
Resampled shape of y:  (568630,)
Counter({0: 284315, 1: 284315})
```

1.8.1 Get train and test data from resampled data

[23]:
```
# Split the data
X_trn_re, X_tst_re, y_trn_re, y_tst_re = train_test_split(X_resampled,␣
 ↪y_resampled, train_size=.8, random_state=42)
X_trn_re, X_vld_re, y_trn_re, y_vld_re = train_test_split(X_trn_re, y_trn_re,␣
 ↪train_size=.8, random_state=42)

print("Resampled shape of X_trn_re: ", X_trn_re.shape)
print("Resampled shape of y_trn_re: ", y_trn_re.shape)
print("Resampled shape of X_vld_re: ", X_vld_re.shape)
print("Resampled shape of y_vld_re: ", y_vld_re.shape)
```

```
print("Resampled shape of X_tst_re: ", X_vld_re.shape)
print("Resampled shape of y_tst_re: ", y_tst_re.shape)
```

```
Resampled shape of X_trn_re:  (363923, 29)
Resampled shape of y_trn_re:  (363923,)
Resampled shape of X_vld_re:  (90981, 29)
Resampled shape of y_vld_re:  (90981,)
Resampled shape of X_tst_re:  (90981, 29)
Resampled shape of y_tst_re:  (113726,)
```

1.9 Decision Tree Classifier Based on oversampled data

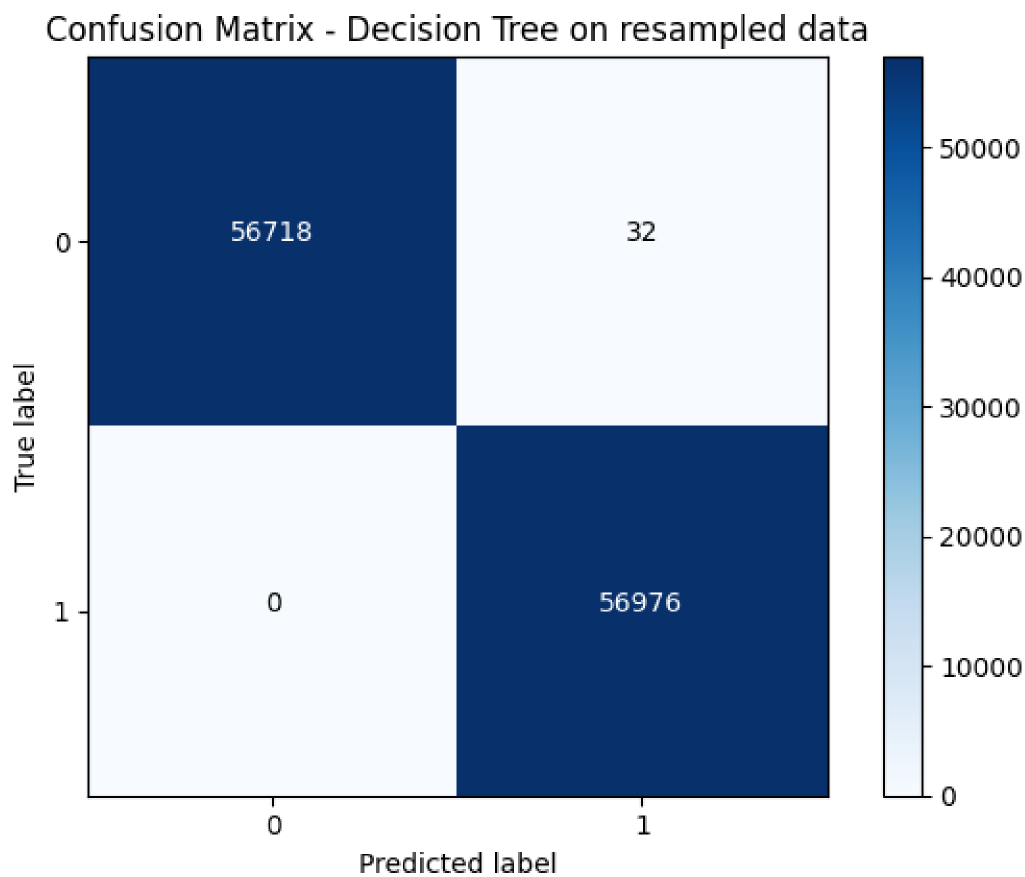
[24]:
```
# Decision Tree Classifier
decision_tree.fit(X_trn_re, y_trn_re)

predictions_dt2 = decision_tree.predict(X_tst_re)
decision_tree_score2 = decision_tree.score(X_tst_re, y_tst_re) * 100
```

[25]:
```
# Plot confusion matrix for Decision Trees
confusion_matrix_dt2 = confusion_matrix(y_tst_re, predictions_dt2.round())
print("Confusion Matrix - Decision Tree")
print(confusion_matrix_dt2)
```

```
Confusion Matrix - Decision Tree
[[56718    32]
 [    0 56976]]
```

[26]:
```
plot_confusion_matrix(confusion_matrix_dt2, classes=[0, 1], title= "Confusion␣
 ↪Matrix - Decision Tree on resampled data")
```

```
Confusion matrix, without normalization
```



[27]:
```
print("Evaluation of Decision Tree Model over resampled data")
print()
metrics_dt2 = metrics(y_tst_re, predictions_dt2.round())
```

```
Evaluation of Decision Tree Model over resampled data

Accuracy: 0.99972
Precision: 0.99944
Recall: 1.00000
F1-score: 0.99972
```

1.10 Neural Network Classifier over resampled data

[28]:
```
model2 = keras.models.Sequential([
    keras.Input(shape=input_shape),
    layers.Flatten(),
    layers.Dense(layer_unit, activation='relu',␣
 ↪kernel_regularizer=model_kernel),
```

```
    layers.Dense(layer_unit, activation='relu',␣
↪kernel_regularizer=model_kernel),
    layers.Dropout(0.2),
    layers.Dense(1, activation='sigmoid')
])

model2.summary()
```

```
Model: "sequential_1"


 Layer (type)                          Output Shape                          ␣
↪Param #

 flatten_1 (Flatten)                   (None, 29)                            ␣
↪  0

 dense_3 (Dense)                       (None, 128)                           ␣
↪3,840

 dense_4 (Dense)                       (None, 128)                           ␣
↪16,512

 dropout_1 (Dropout)                   (None, 128)                           ␣
↪  0

 dense_5 (Dense)                       (None, 1)                             ␣
↪129


 Total params: 20,481 (80.00 KB)

 Trainable params: 20,481 (80.00 KB)

 Non-trainable params: 0 (0.00 B)
```

[29]:
```
model2.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

[30]:
```
# Train the model
history2 = model2.fit(X_trn_re, y_trn_re, epochs=20)
```

```
Epoch 1/20
11373/11373              17s 1ms/step
```

```
- accuracy: 0.9585 - loss: 0.2461
Epoch 2/20
11373/11373             16s 1ms/step
- accuracy: 0.9876 - loss: 0.0733
Epoch 3/20
11373/11373             16s 1ms/step
- accuracy: 0.9903 - loss: 0.0603
Epoch 4/20
11373/11373             16s 1ms/step
- accuracy: 0.9911 - loss: 0.0565
Epoch 5/20
11373/11373             16s 1ms/step
- accuracy: 0.9917 - loss: 0.0528
Epoch 6/20
11373/11373             16s 1ms/step
- accuracy: 0.9912 - loss: 0.0522
Epoch 7/20
11373/11373             17s 1ms/step
- accuracy: 0.9917 - loss: 0.0511
Epoch 8/20
11373/11373             17s 1ms/step
- accuracy: 0.9921 - loss: 0.0498
Epoch 9/20
11373/11373             16s 1ms/step
- accuracy: 0.9922 - loss: 0.0485
Epoch 10/20
11373/11373             17s 1ms/step
- accuracy: 0.9921 - loss: 0.0498
Epoch 11/20
11373/11373             17s 1ms/step
- accuracy: 0.9924 - loss: 0.0484
Epoch 12/20
11373/11373             17s 1ms/step
- accuracy: 0.9923 - loss: 0.0482
Epoch 13/20
11373/11373             17s 1ms/step
- accuracy: 0.9924 - loss: 0.0482
Epoch 14/20
11373/11373             17s 1ms/step
- accuracy: 0.9923 - loss: 0.0475
Epoch 15/20
11373/11373             16s 1ms/step
- accuracy: 0.9928 - loss: 0.0472
Epoch 16/20
11373/11373             17s 1ms/step
- accuracy: 0.9929 - loss: 0.0462
Epoch 17/20
11373/11373             17s 1ms/step
```

```
- accuracy: 0.9933 - loss: 0.0450
Epoch 18/20
11373/11373              17s 1ms/step
- accuracy: 0.9932 - loss: 0.0451
Epoch 19/20
11373/11373              17s 1ms/step
- accuracy: 0.9925 - loss: 0.0465
Epoch 20/20
11373/11373              17s 1ms/step
- accuracy: 0.9929 - loss: 0.0458
```

[31]:

```
model2.predict(X_tst_re)
```

```
3554/3554              2s 620us/step
```

[31]:

```
array([[9.9987364e-01],
       [9.9924558e-01],
       [6.4296324e-09],
       …,
       [9.9922049e-01],
       [9.8870695e-01],
       [1.2334959e-07]], dtype=float32)
```

[32]:

```
loss2, accuracy2 = model2.evaluate(X_tst_re, y_tst_re, verbose=2)
print('Test accuracy after resampling:', accuracy2)
```

```
3554/3554 - 4s - 1ms/step - accuracy: 0.9952 - loss: 0.0388
Test accuracy after resampling: 0.9952077865600586
```

1.11 Summary

Now it is evident that after addressing the class imbalance problem, our Decision Tree classifier performs far better than Decision Tree classifier without oversampling. At the same time, we see that the accuracy of Neutral Network with oversampling slightly degenerate.

[ ]:

```

```