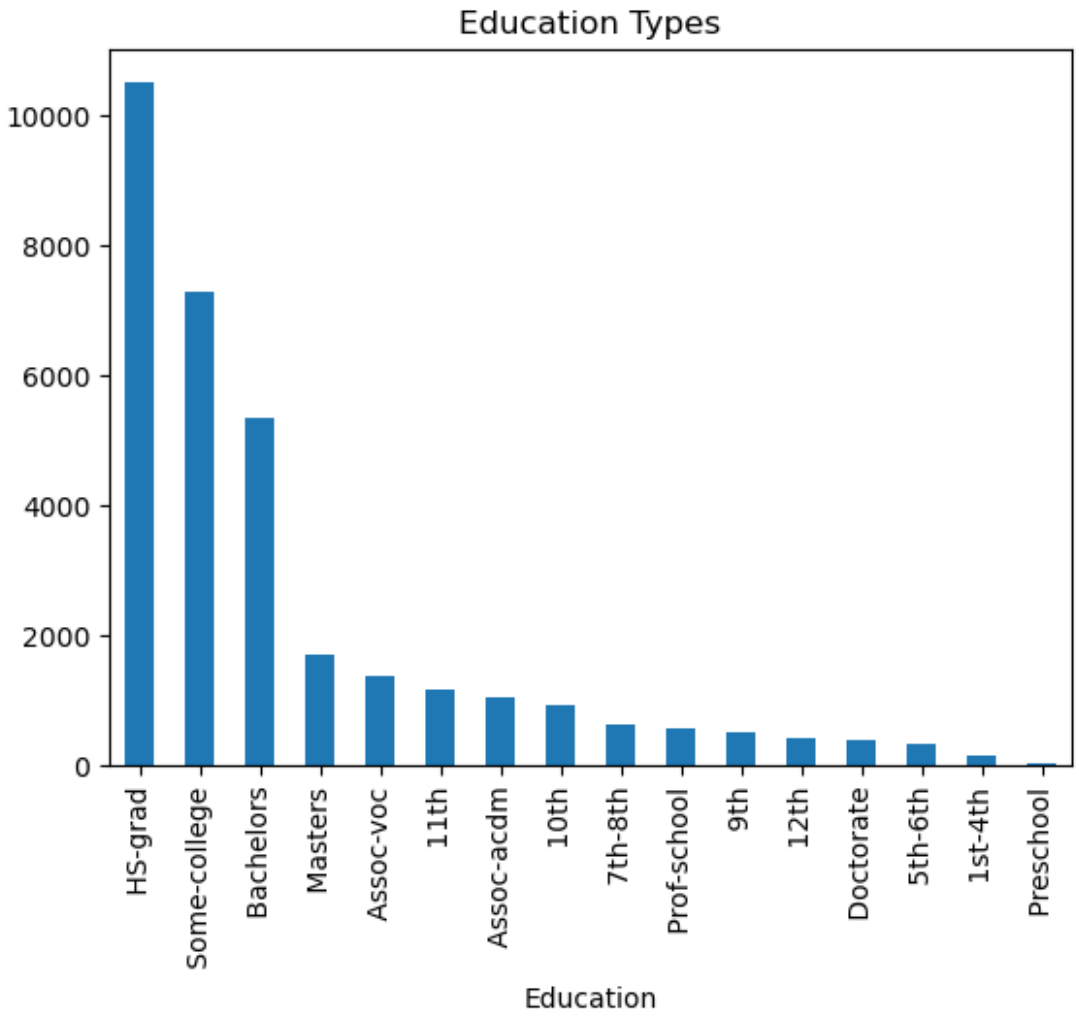
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.discriminant_analysis import StandardScaler
from sklearn.metrics import confusion_matrix, accuracy_score,
precision_score, recall_score, f1_score, ConfusionMatrixDisplay

attributes = ['Age', 'Sector', 'idk', 'Education', 'idk2',
'Marital_Stat', 'Job', 'Family', 'Race', 'Gender', 'idk3', 'idk4',
'Hours/wk', 'Country', 'Income_>50k']

df = pd.read_csv(r"Penghasilan_Orang_Dewasa.csv", header=None)
df.columns = attributes
df.head()
```

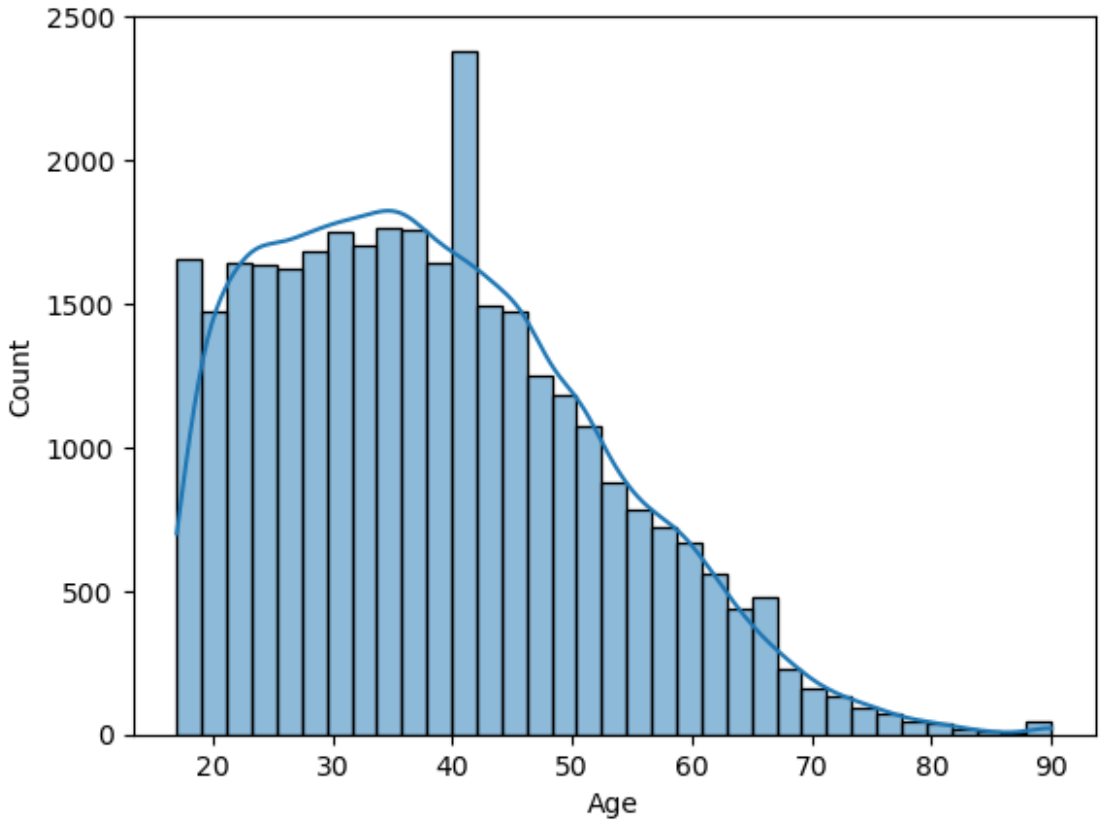
```
   Age             Sector     idk   Education  idk2
Marital_Stat  \
0   39          State-gov   77516   Bachelors    13        Never-
married
1   50   Self-emp-not-inc   83311   Bachelors    13   Married-civ-
spouse
2   38            Private  215646     HS-grad     9
Divorced
3   53            Private  234721        11th     7   Married-civ-
spouse
4   28            Private  338409   Bachelors    13   Married-civ-
spouse

                  Job          Family    Race   Gender  idk3  idk4
Hours/wk  \
0        Adm-clerical   Not-in-family   White     Male  2174     0
40
1     Exec-managerial         Husband   White     Male     0     0
13
2   Handlers-cleaners   Not-in-family   White     Male     0     0
40
3   Handlers-cleaners         Husband   Black     Male     0     0
40
4      Prof-specialty            Wife   Black   Female     0     0
40

          Country Income_>50k
0   United-States       <=50K
1   United-States       <=50K
2   United-States       <=50K
3   United-States       <=50K
4            Cuba       <=50K
```

```
plt.figure()
df['Education'].value_counts().plot(kind='bar')
plt.title('Education Types')
plt.show()
```




```
sns.histplot(data=df, x='Age', bins=35, kde=True)
plt.show()
```

```
C:\Users\Muhammad Triski\anaconda3\Lib\site-packages\seaborn\
_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated
and will be removed in a future version. Convert inf values to NaN
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```




```
sns.histplot(data=df, x='idk', bins=35, kde=True)
plt.show()
```

```
C:\Users\Muhammad Triski\anaconda3\Lib\site-packages\seaborn\
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and will be removed in a future version. Convert inf values to NaN
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```
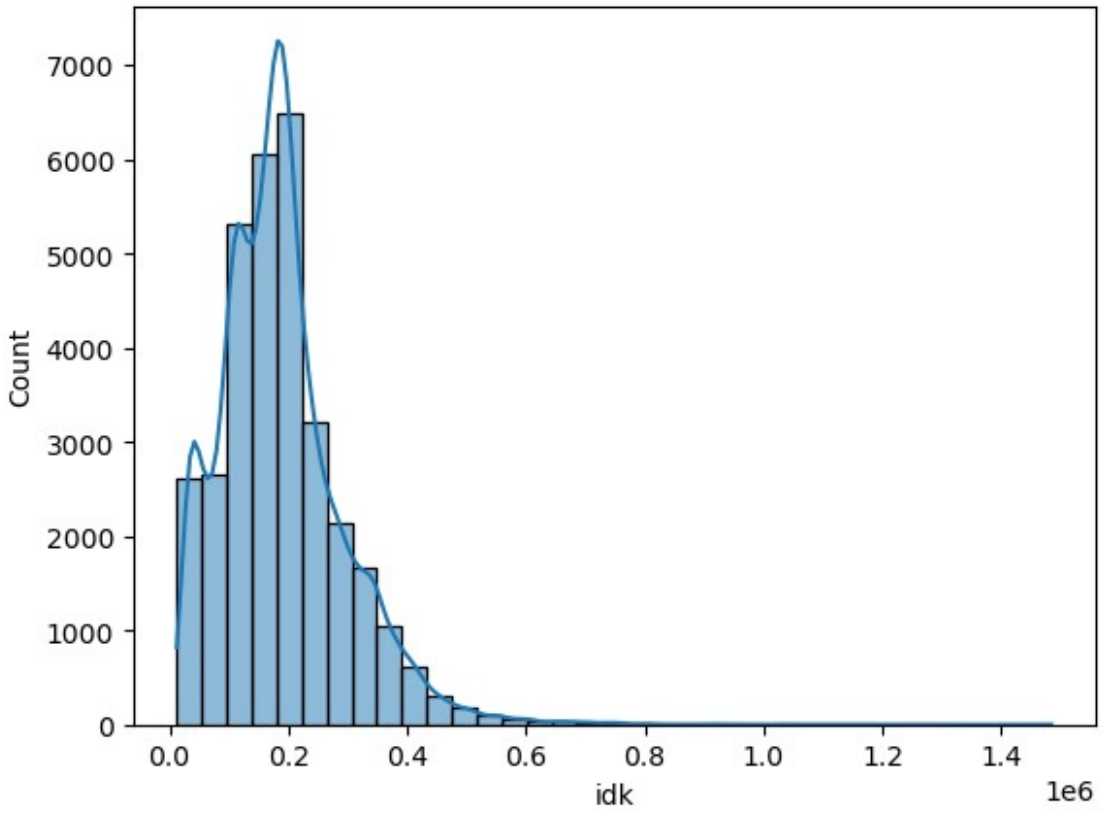
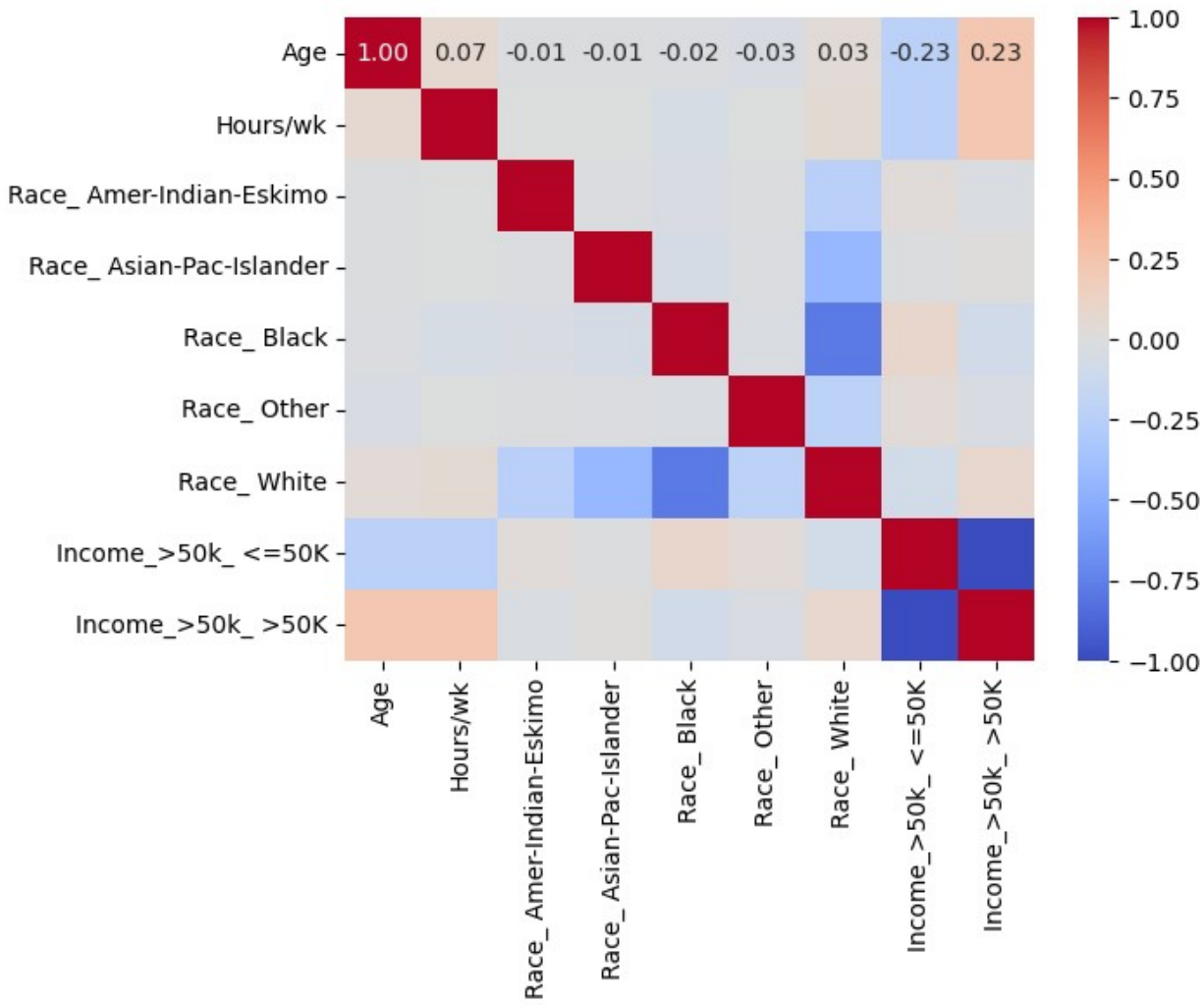




```
df_temp = pd.get_dummies(df[['Age', 'Race', 'Hours/wk',
'Income_>50k']])

corr_matrix = df_temp.corr()

plt.figure()
sns.heatmap(corr_matrix, annot=True, fmt='.2f', cmap='coolwarm',
cbar=True)
plt.show()
```




```
df.replace(' ?', None, inplace=True)
df.isnull().sum()
```

```
Age                0
Sector          1836
idk                0
Education          0
idk2               0
Marital_Stat       0
Job             1843
Family             0
Race               0
Gender             0
idk3               0
idk4               0
Hours/wk           0
Country          583
```

```
Income_>50k         0
dtype: int64
```

```
df.dropna(inplace=True)
try:
    df = df.drop(columns=['idk2', 'idk3', 'idk3', 'idk4'])
except KeyError:
    pass

encoder = LabelEncoder()
df['Income_>50k'] = encoder.fit_transform(df['Income_>50k'])

df['Sector'] = df['Sector'].astype('category').cat.codes
df['Education'] = df['Education'].astype('category').cat.codes
df['Marital_Stat'] = df['Marital_Stat'].astype('category').cat.codes
df['Job'] = df['Job'].astype('category').cat.codes
df['Family'] = df['Family'].astype('category').cat.codes
df['Race'] = df['Race'].astype('category').cat.codes
df['Gender'] = df['Gender'].astype('category').cat.codes
df['Country'] = df['Country'].astype('category').cat.codes

scaler = StandardScaler()
attrs = df.columns[df.columns != 'Income_>50k']
df[attrs] = scaler.fit_transform(df[attrs])

df.head()
```

```
        Age    Sector       idk  Education  Marital_Stat       Job
Family  \
0  0.042796  2.936000 -1.062722  -0.349865      0.947847 -1.479055 -
0.261249
1  0.880288  1.887682 -1.007871  -0.349865     -0.387275 -0.734545 -
0.885737
2 -0.033340 -0.208955  0.244693   0.174763     -1.722396 -0.238206 -
0.261249
3  1.108695 -0.208955  0.425240  -2.448375     -0.387275 -0.238206 -
0.885737
4 -0.794697 -0.208955  1.406658  -0.349865     -0.387275  0.754473
2.236703

       Race    Gender  Hours/wk   Country  Income_>50k
0  0.385048  0.692806 -0.077734  0.264924            0
1  0.385048  0.692806 -2.331531  0.264924            0
2  0.385048  0.692806 -0.077734  0.264924            0
3 -2.011035  0.692806 -0.077734  0.264924            0
4 -2.011035 -1.443405 -0.077734 -5.304034            0
```

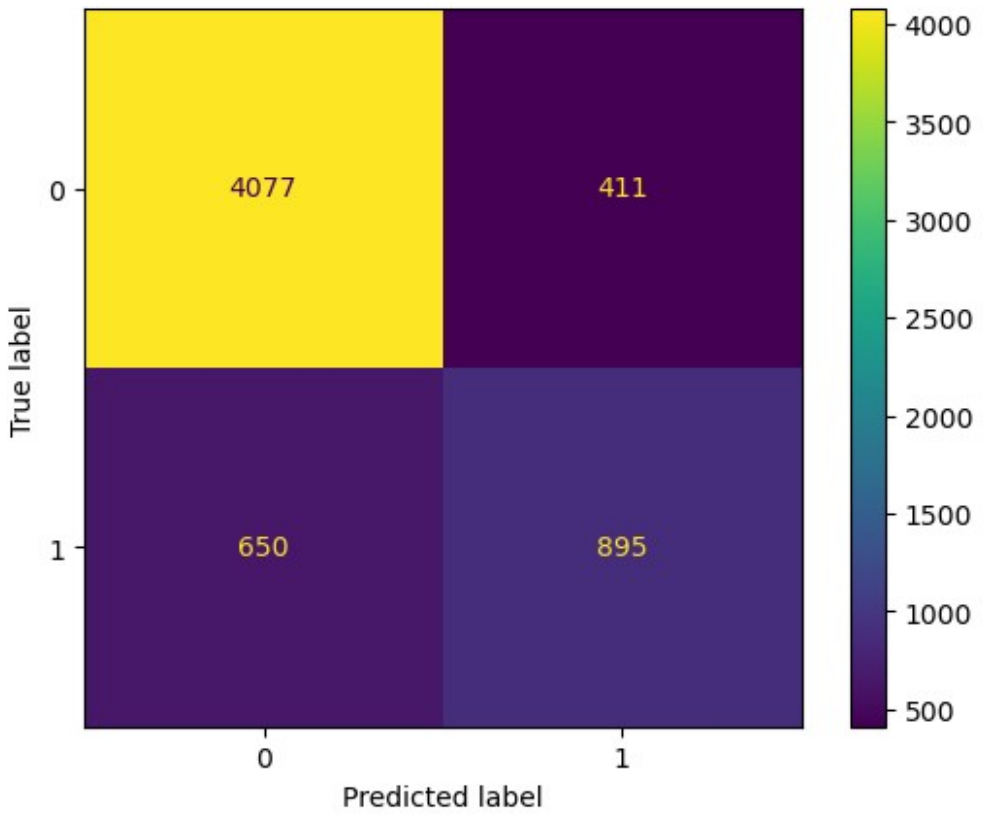
```
#Random forest

X = df.drop('Income_>50k', axis=1)
y = df['Income_>50k']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2)

from sklearn.ensemble import RandomForestClassifier

rf_model = RandomForestClassifier(n_estimators=200)
rf_model.fit(X_train, y_train)
```

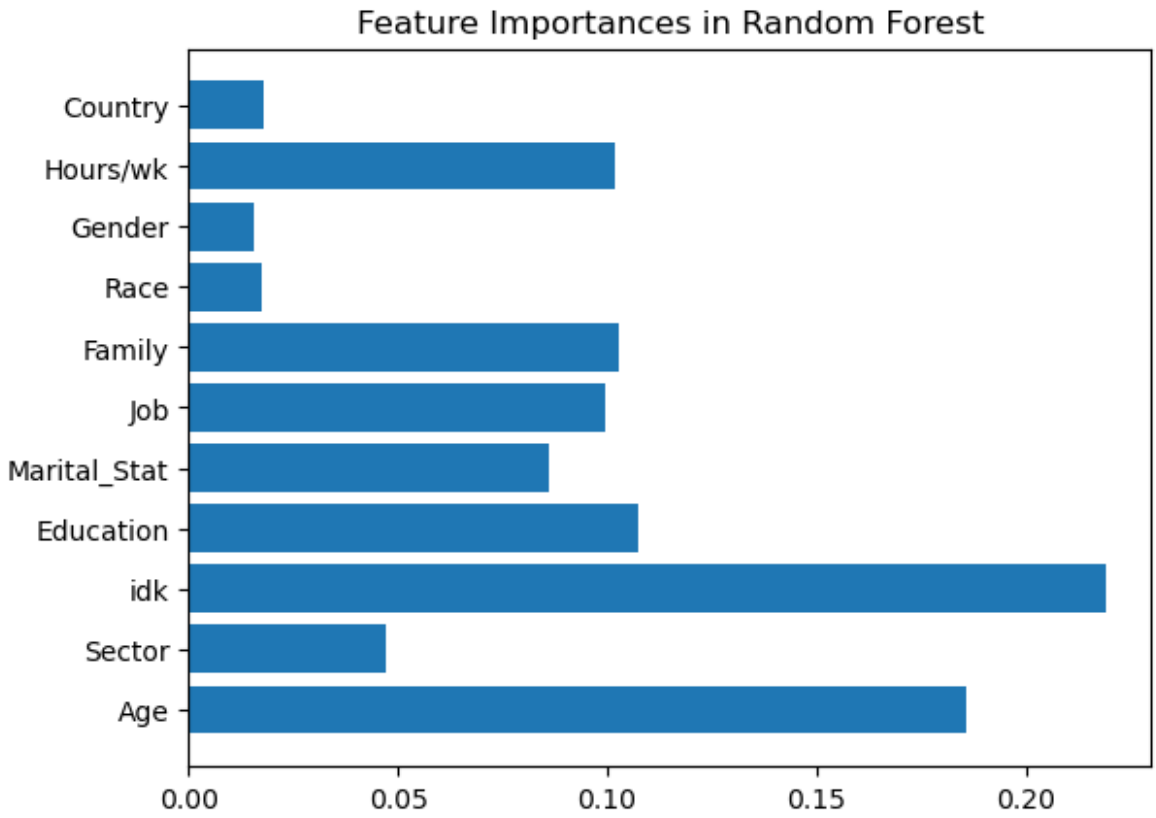
```
RandomForestClassifier(n_estimators=200)
```

```
y_pred = rf_model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print(f'Accuracy: {accuracy:.4f}')
print(f'Precision: {precision:.4f}')
print(f'Recall: {recall:.4f}')
print(f'F1 Score: {f1:.4f}')

cm = confusion_matrix(y_test, y_pred)

disp = ConfusionMatrixDisplay(cm)
disp.plot()
plt.show()
```

```
Accuracy: 0.8241
Precision: 0.6853
Recall: 0.5793
F1 Score: 0.6278
```




```
feature_importances = rf_model.feature_importances_
features = X.columns

importance_df = pd.DataFrame({'Feature': features, 'Importance':
feature_importances})

plt.figure()
plt.barh(importance_df['Feature'], importance_df['Importance'])
plt.title('Feature Importances in Random Forest')
plt.show()
```




```
import torch
print(torch.__version__)
```

```
2.3.1
```

```
import torch
import torch.nn as nn

X_train = torch.tensor(X_train.values, dtype=torch.float32)
y_train = torch.tensor(y_train.values, dtype=torch.float32)
X_train = X_train.clone().detach()
y_train = y_train.clone().detach()

X_test = torch.tensor(X_test.values, dtype=torch.float32)
y_test = torch.tensor(y_test.values, dtype=torch.float32)
X_test = X_train.clone().detach()
y_test = y_train.clone().detach()

X_train.shape
```

```
torch.Size([24129, 11])
```

```
class Model(nn.Module):
    def __init__(self):
        super(Model, self).__init__()
```

```
        self.flatten = nn.Flatten()
        self.linear_relu_stack = nn.Sequential(
            nn.Linear(11, 118),
            nn.ReLU(),
            nn.Linear(118, 118),
            nn.ReLU(),
            nn.Linear(118, 1)
        )

    def forward(self, x):
        x = self.flatten(x)
        logits = self.linear_relu_stack(x)
        logits = torch.sigmoid(logits)
        return logits

model = Model()
print(model)
```

```
Model(
  (flatten): Flatten(start_dim=1, end_dim=-1)
  (linear_relu_stack): Sequential(
    (0): Linear(in_features=11, out_features=118, bias=True)
    (1): ReLU()
    (2): Linear(in_features=118, out_features=118, bias=True)
    (3): ReLU()
    (4): Linear(in_features=118, out_features=1, bias=True)
  )
)
```

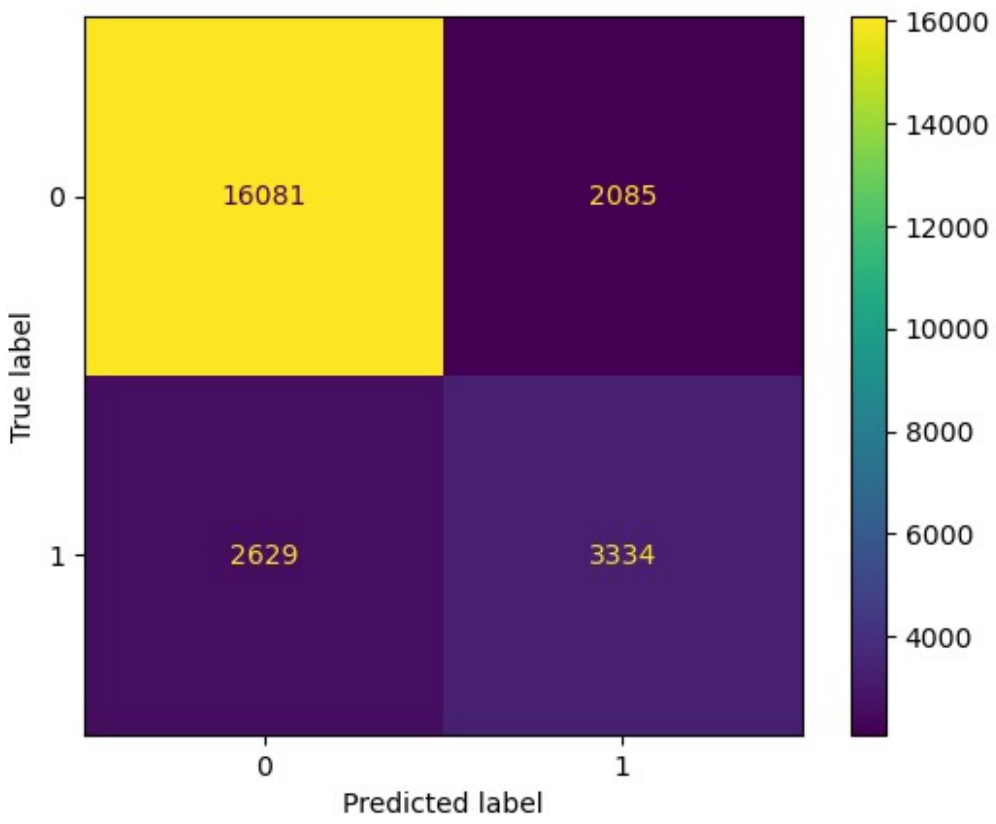
```
criterion = nn.BCELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)

epochs = 200
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    outputs = model(X_train).squeeze()
    loss = criterion(outputs.squeeze(), y_train)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:
        print(f'Epoch [{epoch + 1}/{epochs}], Loss:
{loss.item():.4f}')
```

```
Epoch [10/200], Loss: 0.5498
Epoch [20/200], Loss: 0.5055
Epoch [30/200], Loss: 0.4738
Epoch [40/200], Loss: 0.4590
Epoch [50/200], Loss: 0.4484
```

```
Epoch [60/200], Loss: 0.4397
Epoch [70/200], Loss: 0.4319
Epoch [80/200], Loss: 0.4247
Epoch [90/200], Loss: 0.4181
Epoch [100/200], Loss: 0.4124
Epoch [110/200], Loss: 0.4079
Epoch [120/200], Loss: 0.4046
Epoch [130/200], Loss: 0.4021
Epoch [140/200], Loss: 0.4002
Epoch [150/200], Loss: 0.3985
Epoch [160/200], Loss: 0.3971
Epoch [170/200], Loss: 0.3957
Epoch [180/200], Loss: 0.3943
Epoch [190/200], Loss: 0.3930
Epoch [200/200], Loss: 0.3918
```

```python
model.eval()
y_true = []
y_pred = []

with torch.no_grad():
    outputs = model(X_test)
    predicted = outputs.round()

    y_true = y_test.cpu().numpy()
    y_pred = predicted.cpu().numpy()

y_true = np.array(y_true).flatten()
y_pred = np.array(y_pred).flatten()

accuracy = accuracy_score(y_true, y_pred)
precision = precision_score(y_true, y_pred)
recall = recall_score(y_true, y_pred)
f1 = f1_score(y_true, y_pred)

print(f'Accuracy: {accuracy:.4f}')
print(f'Precision: {precision:.4f}')
print(f'Recall: {recall:.4f}')
print(f'F1 Score: {f1:.4f}')

cm = confusion_matrix(y_true, y_pred)

disp = ConfusionMatrixDisplay(cm)
disp.plot()
plt.show()
```

```
Accuracy: 0.8046
Precision: 0.6152
Recall: 0.5591
F1 Score: 0.5858
```


16081
2085
2629
3334
0
1
True label
0
1
Predicted label
16000
14000
12000
10000
8000
6000
4000