```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import tensorflow as tf
from tensorflow import keras
from keras.models import Sequential
from keras.layers import Dense
from tensorflow.keras import layers, models
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, classification_report
```

```
df = pd.read_csv("/content/creditcard.csv")
df
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.36
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.25
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.5
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.38
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.8
...	...	...	...	...	...	...	...	...	...	
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215	7.305334	1.9
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330	0.294869	0.58
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827	0.708417	0.43
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180	0.679145	0.39
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006	-0.414650	0.48

284807 rows × 31 columns

```
df.drop(['Class'],axis=1)
```

	Time	V1	V2	V3	V4	V5	V6	V7
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.23959
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.07880
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.79146

```
# Drop rows with NaN values in the target column
df = df.dropna(subset=['Class'])

# Standardize the data
scaler = StandardScaler()
X = scaler.fit_transform(df.drop("Class", axis=1))
y = df["Class"]
```

```
xtrain,xtest,ytrain,ytest = train_test_split(X,y,test_size=0.2, random_state=42)
```

```
input_dim=xtrain.shape[1]
```

```
xtrain.shape
```

```
(227845, 30)
```

```
xtest.shape
```

```
(56962, 30)
```

```
encoder = models.Sequential([
    layers.Input(shape=(input_dim,)),
    layers.Dense(32, activation='relu'),
    layers.Dense(16, activation='relu')
])
```

```
decoder = models.Sequential([
      layers.Input(shape=(16,)),
      layers.Dense(30,activation='relu'),
      layers.Dense(input_dim,activation='linear')

])

autoencoder = models.Sequential([
      encoder,
      decoder

])
```

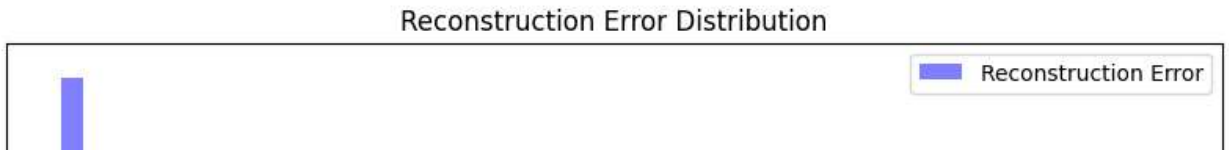
```
autoencoder.compile(optimizer='adam', loss='mean_squared_error')
autoencoder.fit(xtrain, xtrain, epochs=10, batch_size=32, shuffle=True, validation_data=(xtest, xtest))
```

```
Epoch 1/10
7121/7121 [==============================] - 109s 3ms/step - loss: 0.3469 - val_loss: 0.2050
Epoch 2/10
7121/7121 [==============================] - 20s 3ms/step - loss: 0.1784 - val_loss: 0.1475
Epoch 3/10
7121/7121 [==============================] - 23s 3ms/step - loss: 0.1445 - val_loss: 0.1417
Epoch 4/10
7121/7121 [==============================] - 20s 3ms/step - loss: 0.1352 - val_loss: 0.1368
Epoch 5/10
7121/7121 [==============================] - 23s 3ms/step - loss: 0.1284 - val_loss: 0.1214
Epoch 6/10
7121/7121 [==============================] - 19s 3ms/step - loss: 0.1209 - val_loss: 0.1056
Epoch 7/10
7121/7121 [==============================] - 19s 3ms/step - loss: 0.1056 - val_loss: 0.0938
Epoch 8/10
7121/7121 [==============================] - 22s 3ms/step - loss: 0.0975 - val_loss: 0.0902
Epoch 9/10
7121/7121 [==============================] - 19s 3ms/step - loss: 0.0924 - val_loss: 0.0913
Epoch 10/10
7121/7121 [==============================] - 25s 3ms/step - loss: 0.0883 - val_loss: 0.0789
<keras.src.callbacks.History at 0x7b5cf2af6cb0>
```

```
ypred = autoencoder.predict(xtest)
mse = np.mean(np.power(xtest-ypred,2),axis=1)
```

```
1781/1781 [==============================] - 3s 2ms/step
```

```
plt.figure(figsize=(10, 6))
plt.hist(mse, bins=50, alpha=0.5, color='b', label='Reconstruction Error')
plt.xlabel("Reconstruction Error")
plt.ylabel("Frequency")
plt.legend()
plt.title("Reconstruction Error Distribution")
plt.show()
```




```
thresholds = np.arange(0.1,1.0,0.1)

for threshold in thresholds:
  anomalies=mse>threshold
```

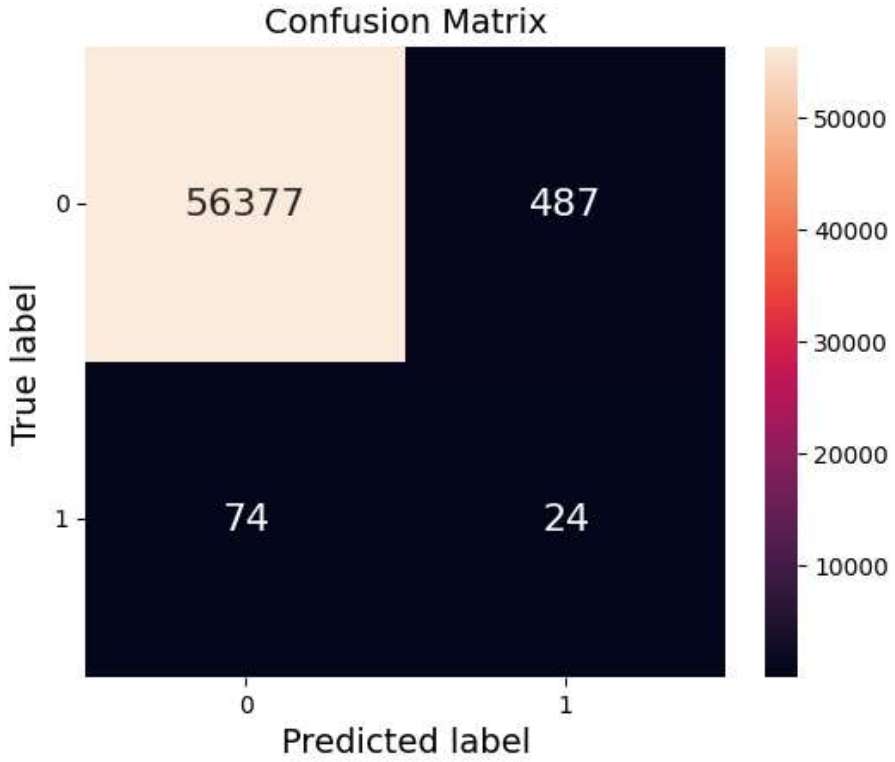
```
num_anomalies = sum(anomalies)
print(f"Threshold: {threshold:.1f}, Number of anomalies :{num_anomalies}")
```

```
Threshold: 0.9, Number of anomalies :511
```

```
print("Confusion Matrix:")
print(confusion_matrix(ytest, anomalies))

print("\nClassification Report:")
print(classification_report(ytest, anomalies))
```

```
Confusion Matrix:
[[56377   487]
 [   74    24]]

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      1.00     56864
           1       0.05      0.24      0.08        98

    accuracy                           0.99     56962
   macro avg       0.52      0.62      0.54     56962
weighted avg       1.00      0.99      0.99     56962
```

```
import seaborn as sns


plt.figure(figsize = (6, 4.75))
sns.heatmap(confusion_matrix(ytest, anomalies), annot = True, annot_kws = {"size": 16}, fmt = 'd')
plt.xticks([0.5, 1.5],  rotation = 'horizontal')
plt.yticks([0.5, 1.5],  rotation = 'horizontal')
plt.xlabel("Predicted label", fontsize = 14)
plt.ylabel("True label", fontsize = 14)
plt.title("Confusion Matrix", fontsize = 14)
plt.grid(False)
plt.show()
```


Confusion Matrix
56377
487
74
24
0
1
True label
0
1
Predicted label
50000
40000
30000
20000
10000