Fraud Analytics (CS6890)

Assignment: 4

Title : Fraud Detection Using an Autoencoder and Variational Autoencoder

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In [4]:
```
import pandas as pd
import numpy as np
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt
import tensorflow as tf
import seaborn as sns
from sklearn.model_selection import train_test_split
from keras.models import Model, load_model
from keras.layers import Input, Dense
from keras.callbacks import ModelCheckpoint, TensorBoard
from keras import regularizers
from tensorflow.keras import models,layers
from tensorflow.keras.models import Model
from sklearn.utils import resample
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tensorflow.keras import layers, models, backend as K
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import MeanSquaredError
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
from sklearn.metrics import (roc_curve,auc)
from sklearn.manifold import TSNE
```

In [5]:
```
# Load the dataset
data = pd.read_csv('creditcard.csv')

# Display the first few rows of the dataset for a quick overview
data.head()
```

Out[5]:

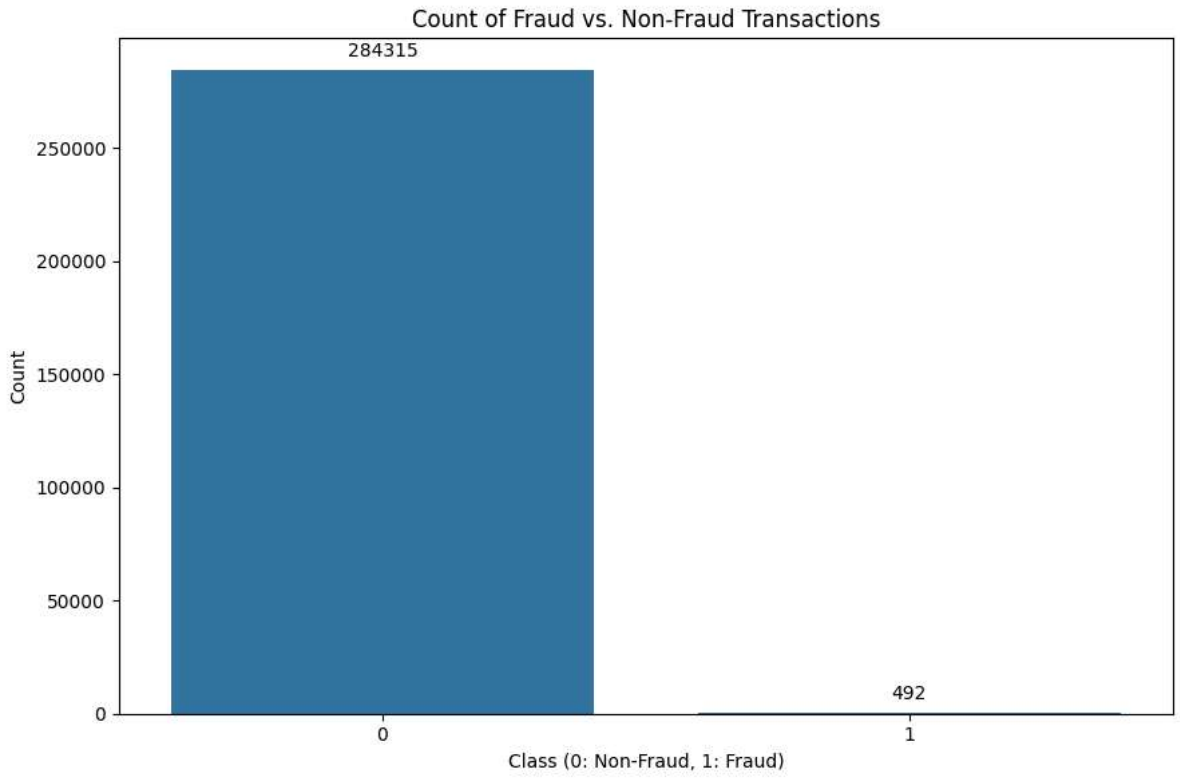
	Time	V1	V2	V3	V4	V5	V6	V7	V8	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0

5 rows × 31 columns

Data Exploration

Here we are plotting a count plot to visualize the distribution of fraud vs. non-fraud transactions in a dataset.

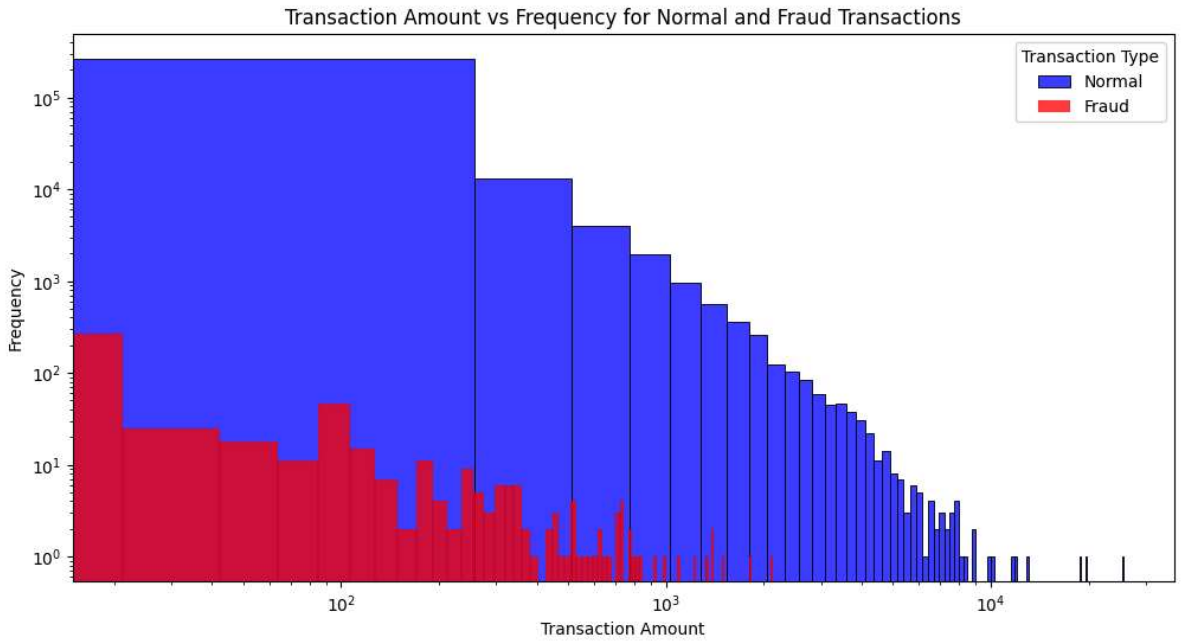
In [6]:
```
# Create the count plot
fig, ax = plt.subplots(figsize=(9, 6))
sns.countplot(x='Class', data=data, ax=ax)

# Set the title, x-label, and y-label
ax.set_title('Count of Fraud vs. Non-Fraud Transactions')
ax.set_xlabel('Class (0: Non-Fraud, 1: Fraud)')
ax.set_ylabel('Count')

# Add count labels above the bars
for p in ax.patches:
    ax.annotate(format(p.get_height(), '.0f'),
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha = 'center', va = 'center',
                xytext = (0, 10),
                textcoords = 'offset points')

# Adjust layout and display the plot
plt.tight_layout()
plt.show()
```



Here we are plotting histogram that visually compares the distribution of transaction amounts for normal and fraud transaction. Here we can detect differences bwtteen the two classes

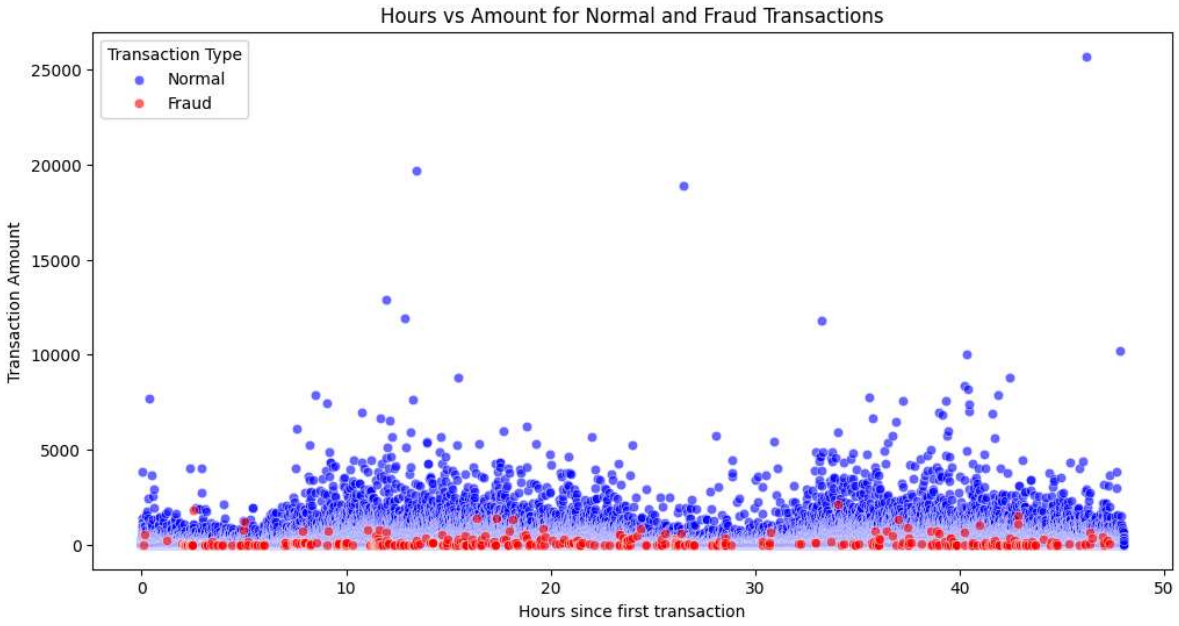
In [7]:

```
# Create a figure for plotting
plt.figure(figsize=(12, 6))

# Plotting transaction amount vs frequency for normal transactions
sns.histplot(data[data['Class'] == 0]['Amount'], bins=100, color='blue', l
sns.histplot(data[data['Class'] == 1]['Amount'], bins=100, color='red', la

plt.title('Transaction Amount vs Frequency for Normal and Fraud Transactio
plt.xlabel('Transaction Amount')
plt.ylabel('Frequency')
plt.legend(title='Transaction Type')
plt.xscale('log')  # Using log scale for better visualization of the spread
plt.yscale('log')  # Log scale for frequency to handle wide range of value
plt.show()
```



In our approach we are converting time into hours and min to do feature selection

In [8]:
```
# Convert 'Time' from seconds to hours to make it more interpretable
data['Hours'] = data['Time'] / 3600

# Create a figure for plotting
plt.figure(figsize=(12, 6))

# Scatter plot of Time vs Amount for normal transactions
sns.scatterplot(x='Hours', y='Amount', data=data[data['Class'] == 0], colo

# Scatter plot of Time vs Amount for fraud transactions
sns.scatterplot(x='Hours', y='Amount', data=data[data['Class'] == 1], colo

plt.title('Hours vs Amount for Normal and Fraud Transactions')
plt.xlabel('Hours since first transaction')
plt.ylabel('Transaction Amount')
plt.legend(title='Transaction Type')
plt.show()

data = data.drop('Hours', axis=1)
```



The graph doesn't reveal much about the relationship between fraudulent transactions and the time they occurred. Therefore, we are dropping the 'Time' column.

Data Preprocessing

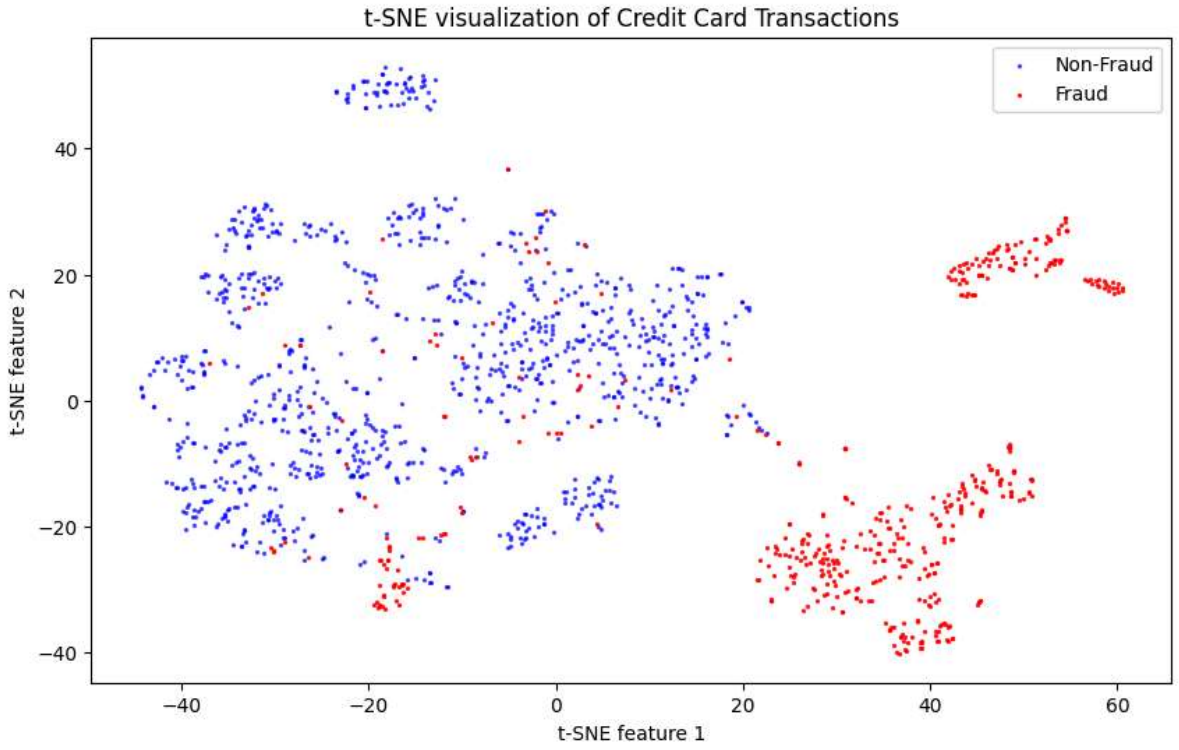
In [ ]:

```
# Convert 'Time' and 'Amount' to log scale to compress dynamic range
# Adding 1 before taking the log to avoid log(0)

data['Log_Amount'] = np.log(data['Amount'] + 1)

# Drop the original 'Time' and 'Amount' columns
data.drop(['Time', 'Amount'], axis=1, inplace=True)

# Standardize the newly created log features
scaler = StandardScaler()
data[['Log_Amount']] = scaler.fit_transform(data[['Log_Amount']])


# Splitting the dataset into training and test sets
# Separating features (X) and target variable (y)
X = data.drop('Class', axis=1)
y = data['Class']

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

# Overview of the split
X_train.shape, X_test.shape
```

Out[24]: ((227845, 29), (56962, 29))

In [ ]:

```
# Sample for visualizations and model training
non_fraud = data[data['Class'] == 0].sample(1000, random_state=42)
fraud = data[data['Class'] == 1]
df = pd.concat([non_fraud, fraud]).sample(frac=1, random_state=42).reset_i
X = df.drop(['Class'], axis=1).values
Y = df['Class'].values


# Assuming tsne_plot is a function that you have defined to plot t-SNE vis


### Utility Functions
def tsne_plot(X, Y, filename):
    tsne = TSNE(n_components=2, random_state=42)
    X_tsne = tsne.fit_transform(X)
    plt.figure(figsize=(10, 6))
    plt.scatter(X_tsne[Y == 0, 0], X_tsne[Y == 0, 1], label='Non-Fraud', a
    plt.scatter(X_tsne[Y == 1, 0], X_tsne[Y == 1, 1], label='Fraud', alpha
    plt.title('t-SNE visualization of Credit Card Transactions')
    plt.xlabel('t-SNE feature 1')
    plt.ylabel('t-SNE feature 2')
    plt.legend()
    plt.savefig(filename)
    plt.show()


tsne_plot(X, Y, "original.png")
```



In [ ]:
```
# Assuming y_test is a series with binary labels where 1 represents fraud
num_fraud_cases = sum(y_test)
num_non_fraud_cases = len(y_test) - num_fraud_cases

# Filter the test set to include only the fraud cases
X_test_fraud = X_test[y_test == 1]

# Sample an equal number of non-fraud cases from the test set
X_test_non_fraud = X_test[y_test == 0].sample(n=num_fraud_cases, random_st

# Combine the fraud and non-fraud cases to form the final test set
X_test_final = pd.concat([X_test_fraud, X_test_non_fraud])
y_test_final = pd.Series(np.where(X_test_final.index.isin(X_test_fraud.inc

# Verify the class distribution in the final test set
print("Class distribution in the final test set:")
print(y_test_final.value_counts())

# Optionally, shuffle the test set
# To shuffle the data correctly, use the sklearn shuffle utility
from sklearn.utils import shuffle
X_test_final, y_test_final = shuffle(X_test_final, y_test_final, random_st
```

```
Class distribution in the final test set:
1    98
0    98
Name: count, dtype: int64
```

AutoEncoder

Architecher

In [ ]:
```
input_dim = X_train.shape[1]
encoding_dim = 14
input_layer = Input(shape=(input_dim, ))
encoder = Dense(encoding_dim, activation="tanh",
                activity_regularizer=regularizers.l1(10e-5))(input_layer)
encoder = Dense(int(encoding_dim / 2), activation="relu")(encoder)
decoder = Dense(int(encoding_dim / 2), activation='tanh')(encoder)
decoder = Dense(input_dim, activation='relu')(decoder)
autoencoder = Model(inputs=input_layer, outputs=decoder)
```

In [ ]:
```
1 autoencoder.summary()
```

Model: "functional_3"

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 29)	0
dense_4 (Dense)	(None, 14)	420
dense_5 (Dense)	(None, 7)	105
dense_6 (Dense)	(None, 7)	56
dense_7 (Dense)	(None, 29)	232

Total params: 813 (3.18 KB)

Trainable params: 813 (3.18 KB)

Non-trainable params: 0 (0.00 B)

Training

In [ ]:

```
nb_epoch = 50
batch_size = 256
autoencoder.compile(optimizer='adam',
                    loss='mean_squared_error',
                    metrics=['accuracy'])
checkpointer = ModelCheckpoint(filepath="model.keras",
                               verbose=0,
                               save_best_only=True)
tensorboard = TensorBoard(log_dir='./logs',
                          histogram_freq=0,
                          write_graph=True,
                          write_images=True)
history = autoencoder.fit(X_train, X_train,
                    epochs=nb_epoch,
                    batch_size=batch_size,
                    shuffle=True,
                    validation_data=(X_test, X_test),
                    verbose=1,
                    callbacks=[checkpointer, tensorboard]).history
```

```
Epoch 1/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step - accuracy: 0.2410 - loss: 1.1436 -
val_accuracy: 0.5526 - val_loss: 0.9135
Epoch 2/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.5678 - loss: 0.8721 -
val_accuracy: 0.5784 - val_loss: 0.8578
Epoch 3/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.5857 - loss: 0.8364 -
val_accuracy: 0.5973 - val_loss: 0.8414
Epoch 4/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6003 - loss: 0.8548 -
val_accuracy: 0.6025 - val_loss: 0.8342
Epoch 5/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6031 - loss: 0.8376 -
val_accuracy: 0.6059 - val_loss: 0.8310
Epoch 6/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6024 - loss: 0.8271 -
val_accuracy: 0.5960 - val_loss: 0.8296
Epoch 7/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6027 - loss: 0.8299 -
val_accuracy: 0.5986 - val_loss: 0.8241
Epoch 8/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6070 - loss: 0.8171 -
val_accuracy: 0.6212 - val_loss: 0.8111
Epoch 9/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6268 - loss: 0.8324 -
val_accuracy: 0.6299 - val_loss: 0.8032
Epoch 10/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6305 - loss: 0.7893 -
val_accuracy: 0.6369 - val_loss: 0.8045
Epoch 11/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6327 - loss: 0.7905 -
val_accuracy: 0.6336 - val_loss: 0.7963
Epoch 12/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6320 - loss: 0.8069 -
val_accuracy: 0.6317 - val_loss: 0.7963
Epoch 13/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6319 - loss: 0.7992 -
val_accuracy: 0.6247 - val_loss: 0.8010
Epoch 14/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6318 - loss: 0.8007 -
val_accuracy: 0.6332 - val_loss: 0.7937
Epoch 15/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6331 - loss: 0.7951 -
val_accuracy: 0.6276 - val_loss: 0.7926
Epoch 16/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6332 - loss: 0.7868 -
val_accuracy: 0.6008 - val_loss: 0.8050
Epoch 17/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6303 - loss: 0.7886 -
val_accuracy: 0.6367 - val_loss: 0.7920
Epoch 18/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6328 - loss: 0.7957 -
val_accuracy: 0.6202 - val_loss: 0.7917
Epoch 19/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6325 - loss: 0.7770 -
val_accuracy: 0.6280 - val_loss: 0.7923
```

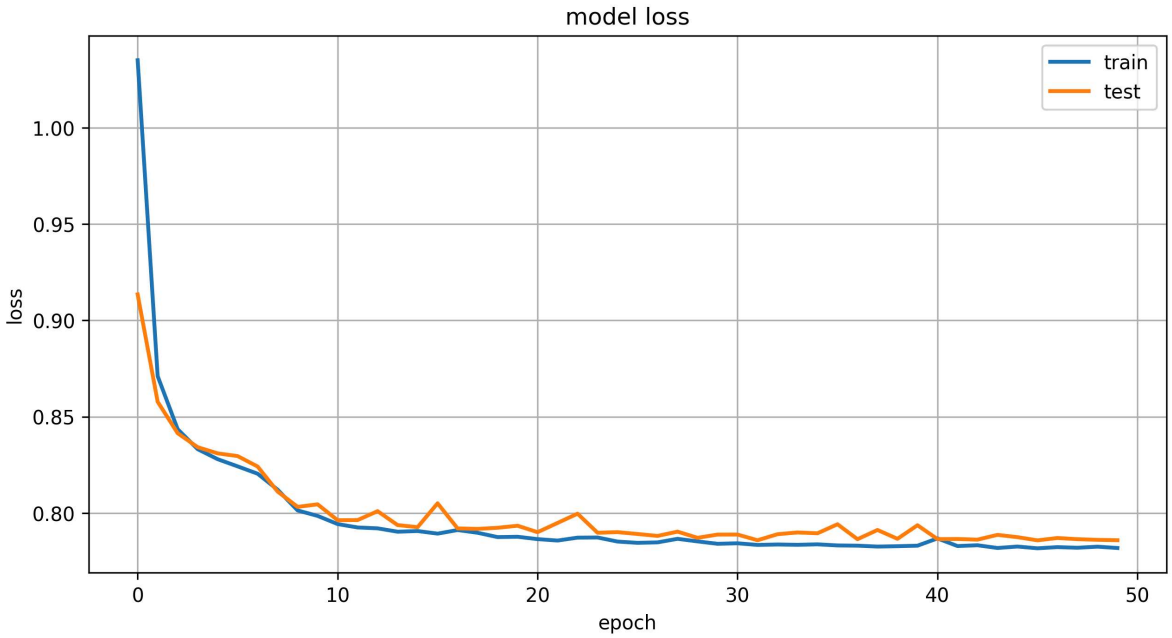
```
Epoch 20/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6325 - loss: 0.7985 -
val_accuracy: 0.6348 - val_loss: 0.7934
Epoch 21/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6312 - loss: 0.7898 -
val_accuracy: 0.6307 - val_loss: 0.7900
Epoch 22/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6354 - loss: 0.7926 -
val_accuracy: 0.6312 - val_loss: 0.7948
Epoch 23/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6351 - loss: 0.7759 -
val_accuracy: 0.6207 - val_loss: 0.7997
Epoch 24/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6291 - loss: 0.7906 -
val_accuracy: 0.6415 - val_loss: 0.7897
Epoch 25/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.6355 - loss: 0.7848 -
val_accuracy: 0.6318 - val_loss: 0.7901
Epoch 26/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6345 - loss: 0.7805 -
val_accuracy: 0.6361 - val_loss: 0.7891
Epoch 27/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6337 - loss: 0.7805 -
val_accuracy: 0.6282 - val_loss: 0.7881
Epoch 28/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6331 - loss: 0.7641 -
val_accuracy: 0.6377 - val_loss: 0.7903
Epoch 29/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6349 - loss: 0.8123 -
val_accuracy: 0.6427 - val_loss: 0.7871
Epoch 30/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6350 - loss: 0.7750 -
val_accuracy: 0.6381 - val_loss: 0.7888
Epoch 31/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6331 - loss: 0.7925 -
val_accuracy: 0.6335 - val_loss: 0.7888
Epoch 32/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6368 - loss: 0.7784 -
val_accuracy: 0.6353 - val_loss: 0.7859
Epoch 33/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6359 - loss: 0.7775 -
val_accuracy: 0.6295 - val_loss: 0.7890
Epoch 34/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6343 - loss: 0.7783 -
val_accuracy: 0.6331 - val_loss: 0.7899
Epoch 35/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6347 - loss: 0.7829 -
val_accuracy: 0.6325 - val_loss: 0.7895
Epoch 36/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6360 - loss: 0.7927 -
val_accuracy: 0.6208 - val_loss: 0.7942
Epoch 37/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6363 - loss: 0.7878 -
val_accuracy: 0.6329 - val_loss: 0.7864
Epoch 38/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6347 - loss: 0.7755 -
val_accuracy: 0.6378 - val_loss: 0.7912
```

```
Epoch 39/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6367 - loss: 0.7818 -
val_accuracy: 0.6391 - val_loss: 0.7866
Epoch 40/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6362 - loss: 0.7831 -
val_accuracy: 0.6282 - val_loss: 0.7936
Epoch 41/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6302 - loss: 0.8044 -
val_accuracy: 0.6380 - val_loss: 0.7865
Epoch 42/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6369 - loss: 0.7820 -
val_accuracy: 0.6310 - val_loss: 0.7865
Epoch 43/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6323 - loss: 0.7914 -
val_accuracy: 0.6397 - val_loss: 0.7862
Epoch 44/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6364 - loss: 0.7846 -
val_accuracy: 0.6289 - val_loss: 0.7886
Epoch 45/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6392 - loss: 0.7938 -
val_accuracy: 0.6341 - val_loss: 0.7875
Epoch 46/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6354 - loss: 0.7919 -
val_accuracy: 0.6407 - val_loss: 0.7858
Epoch 47/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6375 - loss: 0.7925 -
val_accuracy: 0.6249 - val_loss: 0.7870
Epoch 48/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6367 - loss: 0.7788 -
val_accuracy: 0.6507 - val_loss: 0.7864
Epoch 49/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6376 - loss: 0.7799 -
val_accuracy: 0.6307 - val_loss: 0.7861
Epoch 50/50
891/891 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6383 - loss: 0.7836 -
val_accuracy: 0.6310 - val_loss: 0.7859
```

In [ ]:

```
1 autoencoder = load_model('model.keras')
```

In [ ]:
```
plt.figure(figsize=(10, 5), dpi=300)  # Setting the figure size and dpi fo
plt.plot(history['loss'], label='train', linewidth=2)
plt.plot(history['val_loss'], label='test', linewidth=2)
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(loc='upper right')
plt.grid(True)
plt.show()
```

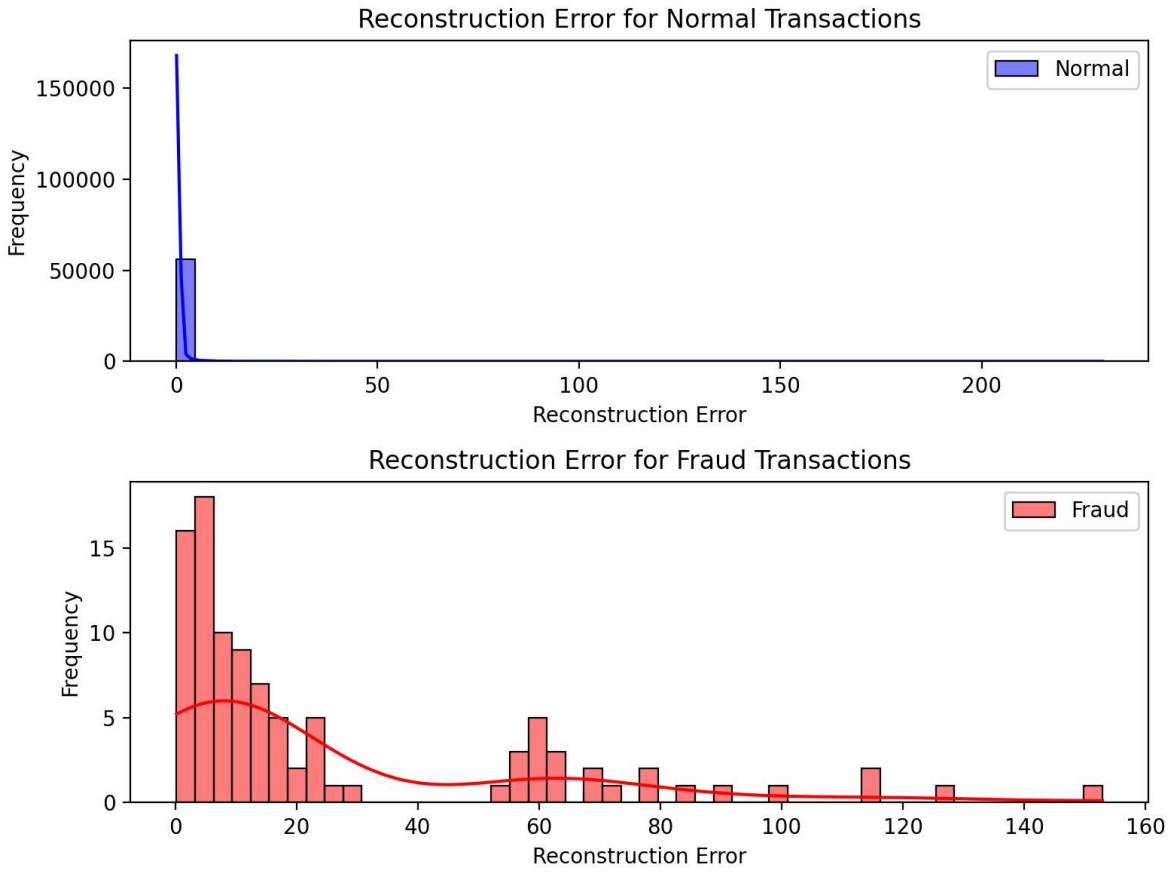


In [ ]:
```
predictions = autoencoder.predict(X_test)
mse = np.mean(np.power(X_test - predictions, 2), axis=1)
```

1781/1781 ━━━━━━━━━━━━━━━━━━━━ **1s** 473us/step

In [ ]:

```
# Separate the reconstruction error by class
mse_normal = mse[y_test == 0]
mse_fraud = mse[y_test == 1]

# Using the same mock data for demonstration purposes
# Normally you would replace 'mse_normal' and 'mse_fraud' with your actual

# Create subplots
fig, ax = plt.subplots(2, 1, figsize=(8, 6), dpi=200)

# Histogram of reconstruction errors for normal transactions
sns.histplot(mse_normal, bins=50, kde=True, color='blue', label='Normal',
ax[0].set_title('Reconstruction Error for Normal Transactions')
ax[0].set_xlabel('Reconstruction Error')
ax[0].set_ylabel('Frequency')
ax[0].legend()

# Histogram of reconstruction errors for fraud transactions
sns.histplot(mse_fraud, bins=50, kde=True, color='red', label='Fraud', ax=
ax[1].set_title('Reconstruction Error for Fraud Transactions')
ax[1].set_xlabel('Reconstruction Error')
ax[1].set_ylabel('Frequency')
ax[1].legend()

plt.tight_layout()
plt.show()
```

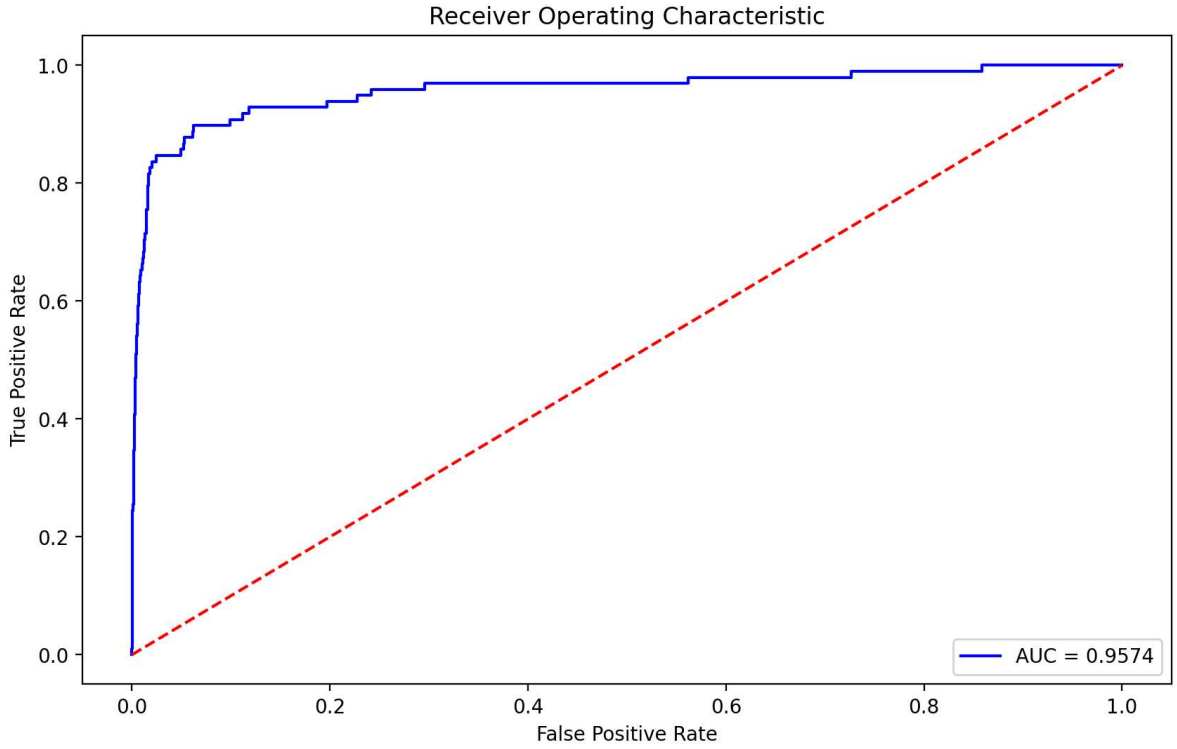


Results

ROC curve

The ROC curve below represents the performance of a classification model, with an AUC (Area Under the Curve) of 0.9574, indicating a high level of accuracy. The true positive rate is high across different thresholds, while maintaining a low false positive rate. This model is effective at distinguishing between the classes (e.g., fraud and non-fraud).

In [ ]:
```
# Compute ROC curve and ROC area for the test set
fpr, tpr, thresholds = roc_curve(y_test, mse)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(10, 6), dpi=200)
plt.plot(fpr, tpr, color='blue', label=f'AUC = {roc_auc:.4f}')
plt.plot([0, 1], [0, 1], color='red', linestyle='--')
plt.title('Receiver Operating Characteristic')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc='lower right')
plt.show()
```

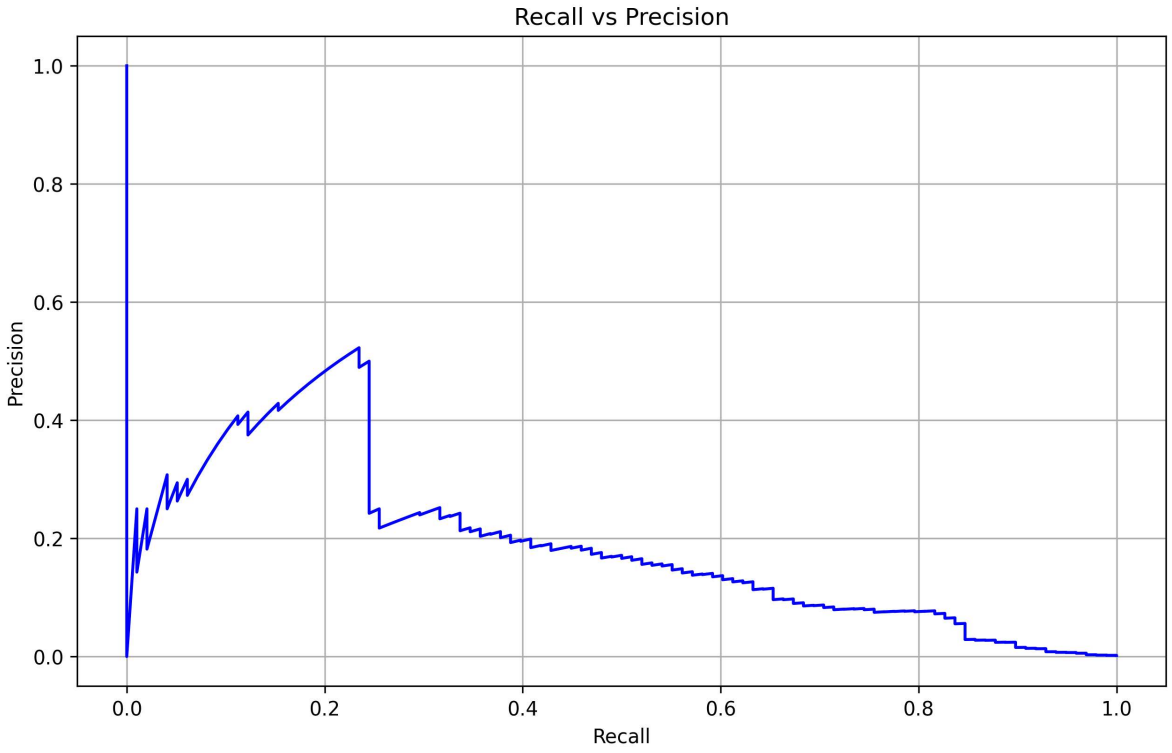


In [ ]:
```
from sklearn.metrics import (confusion_matrix, precision_recall_curve, auc
                             roc_curve, recall_score, classification_repor
                             precision_recall_fscore_support)
```

Recall vs Precision

The Precision-Recall curve below shows the trade-off between precision and recall for a classification model at different thresholds. High precision near the y-axis suggests that the model is accurate when it predicts positive classes, but recall drops quickly, indicating it doesn't capture all positive cases. The model is precise but not highly sensitive to all positives.

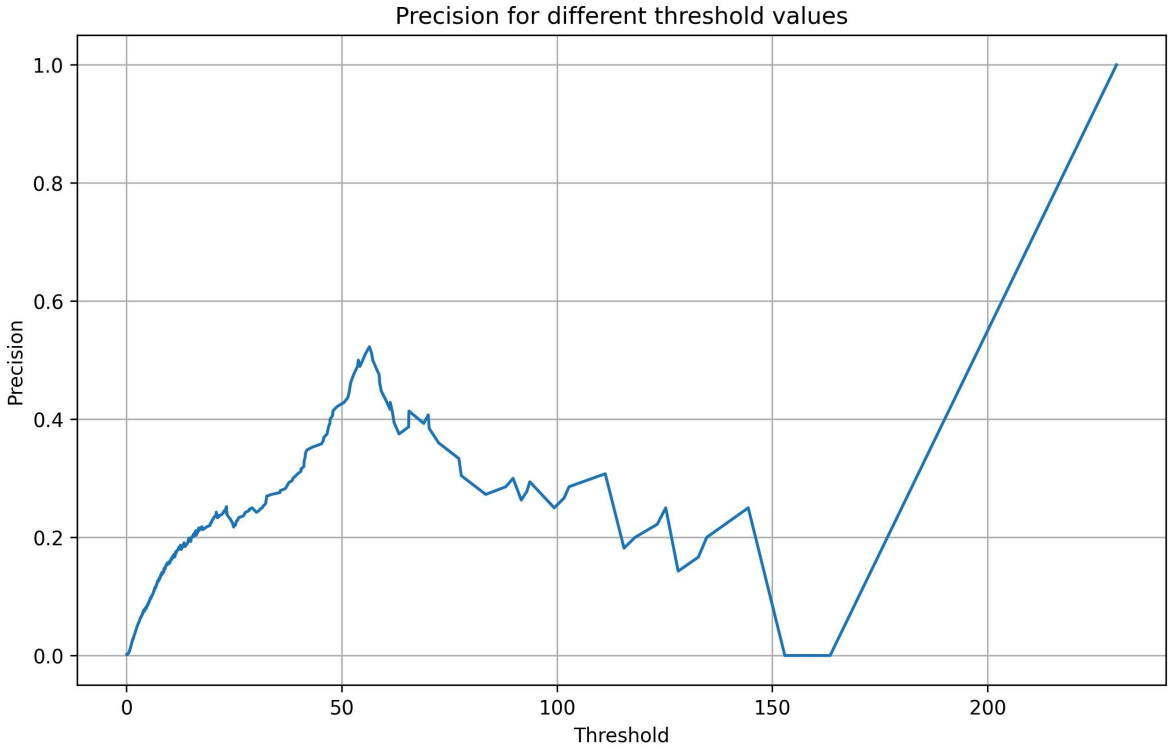
In [ ]:
```
precision, recall, th = precision_recall_curve(y_test, mse)
plt.figure(figsize=(10, 6), dpi=300)
plt.plot(recall, precision,  'b')
plt.title('Recall vs Precision')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.grid(True)
plt.show()
```



Precision for different threshold values

The graph shows how the precision of a predictive model varies with different threshold values. As the threshold increases, precision fluctuates and tends to decrease before shooting up to perfect precision at the highest threshold. This suggests that the model becomes very selective, possibly only predicting positives when very sure, which may not be practical if high recall is also desired.

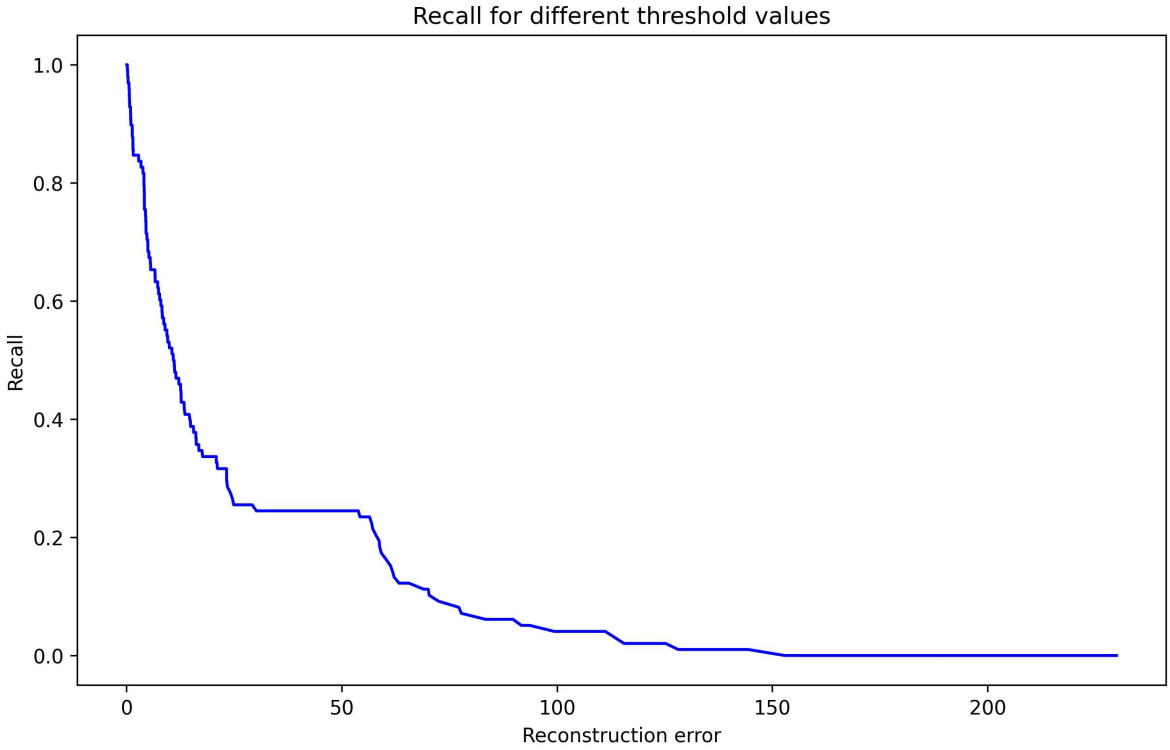
In [ ]:
```
plt.figure(figsize=(10, 6), dpi=300)
plt.plot(th, precision[1:])
plt.title('Precision for different threshold values')
plt.xlabel('Threshold')
plt.ylabel('Precision')
plt.grid(True)
plt.show()
```



Threshold-Recall curve

The graph illustrates recall as a function of varying reconstruction error thresholds in a predictive model. Initially, recall is high, indicating most positive cases are captured, but it declines sharply as the threshold increases, implying fewer positives are detected. At high threshold levels, recall is low, suggesting many positive instances are missed by the model.

In [ ]:
```
plt.figure(figsize=(10, 6), dpi=300)
plt.plot(th, recall[1:], 'b', label='Threshold-Recall curve')
plt.title('Recall for different threshold values')
plt.xlabel('Reconstruction error')
plt.ylabel('Recall')
plt.show()
```



F1 SCORE

The calculation of the optimal threshold that maximizes the F1 score involves these concise mathematical steps:

1. **Precision and Recall Calculation**:
   - Generate a set of predictions or error scores (S).
   - Use the function `precision_recall_curve(y, S)` to obtain precision ((P)) and recall ((R)) values at various thresholds ((T)) derived from (S).
2. **F1 Score Calculation for Each Threshold**:
   - For each threshold (t) in (T), calculate the F1 score: $$ F1(t) = 2 \times \frac{P(t) \times R(t)}{P(t) + R(t)} $$
   - This formula ensures that the F1 score is computed for each possible threshold based on the corresponding precision and recall values.
3. **Optimal Threshold Determination**:
   - Identify the threshold (t_{\text{opt}}) that maximizes (F1(t)): $$ t_{\text{opt}} = \text{argmax} \, F1(t) $$
   - Here, (\text{argmax}) is the operation that finds the argument (threshold) that results in the maximum F1 score.

4. **Using the Optimal Threshold**:

   - With (t_{\text{opt}}) known, classify future data points by comparing their score (s) against (t_{\text{opt}}).

This process effectively balances precision and recall, yielding the most reliable threshold for making binary decisions in various applications, particularly when handling skewed datasets.

In [ ]:

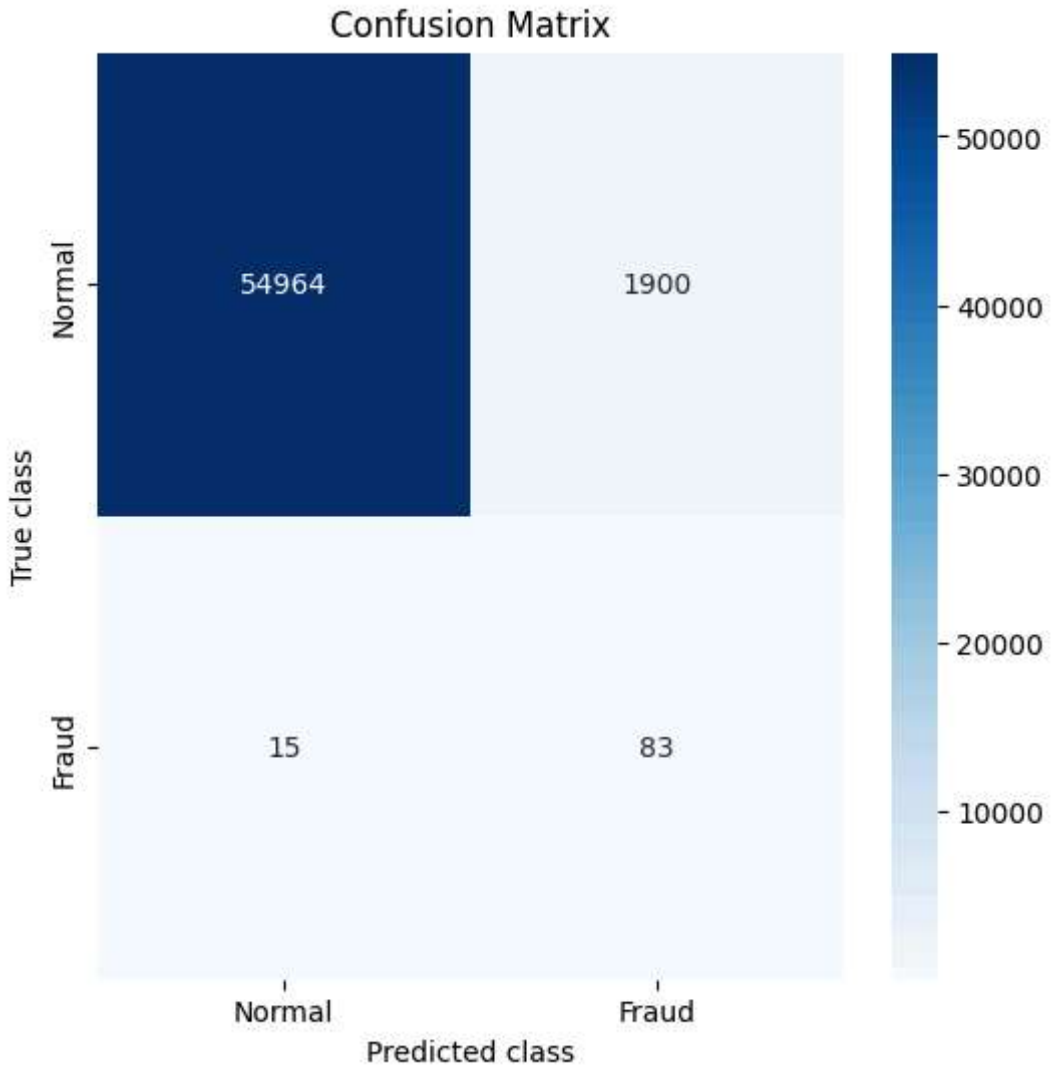
```
predictions = autoencoder.predict(X_test_final)

mse_final = np.mean(np.power(X_test_final - predictions, 2), axis=1)



precision, recall, thresholds = precision_recall_curve(y_test_final, mse_f


# Calculate F1 scores for each possible threshold
f1_scores = 2 * (precision * recall) / (precision + recall)

# Find the index of the maximum F1 score
optimal_idx = np.nanargmax(f1_scores)


optimal_threshold = thresholds[optimal_idx]
optimal_f1 = f1_scores[optimal_idx]

print("Optimal Threshold:", optimal_threshold)
print("Maximum F1 Score:", optimal_f1)

# Convert reconstruction error to binary predictions
binary_predictions = [1 if error > optimal_threshold else 0 for error in r

# Calculate F1 score
final_f1_score = f1_score(y_test_final, binary_predictions)

print("F1 score:", final_f1_score)

```

```
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 833us/step
Optimal Threshold: 1.0259181923459462
Maximum F1 Score: 0.9175257731958762
F1 score: 0.9119170984455959
```

Confusion matrix

This confusion matrix shows that for a binary classification problem, the classifier correctly identified 54,964 normal cases and 83 fraud cases. However, it incorrectly classified 1,900 normal cases as fraud (false positives) and failed to identify 15 fraud cases (false negatives). The matrix suggests the model is relatively good at detecting normal cases but less effective at identifying fraud.

In [80]:
```
LABELS = ["Normal", "Fraud"]

# Confusion Matrix
prediction = [1 if e > optimal_threshold else 0 for e in mse]
conf_matrix = confusion_matrix(y_test, prediction)

plt.figure(figsize=(6, 6))
sns.heatmap(conf_matrix, xticklabels=LABELS, yticklabels=LABELS, annot=Tru
plt.title("Confusion Matrix")
plt.ylabel('True class')
plt.xlabel('Predicted class')
plt.show()
```



VAE

Architecture

Training

In [ ]:

```
class Sampling(layers.Layer):
    """Uses (z_mean, z_log_var) to sample z, the vector encoding a digit.'
    def call(self, inputs):
        z_mean, z_log_var = inputs
        batch = tf.shape(z_mean)[0]
        dim = tf.shape(z_mean)[1]
        epsilon = K.random_normal(shape=(batch, dim))
        return z_mean + tf.exp(0.5 * z_log_var) * epsilon

# Define encoder model.
input_dim = X_train.shape[1]
latent_dim = 2

encoder_inputs = layers.Input(shape=(input_dim,))
x = layers.Dense(64, activation='relu')(encoder_inputs)  # Increased to 64
x = layers.Dense(128, activation='relu')(x)              # Added another l
z_mean = layers.Dense(latent_dim, name='z_mean')(x)
z_log_var = layers.Dense(latent_dim, name='z_log_var')(x)
z = Sampling()([z_mean, z_log_var])
encoder = models.Model(encoder_inputs, [z_mean, z_log_var, z], name='encod

# Increase the width and depth of the decoder as well.
latent_inputs = layers.Input(shape=(latent_dim,), name='z_sampling')
x = layers.Dense(128, activation='relu')(latent_inputs)  # Matched with en
x = layers.Dense(64, activation='relu')(x)               # Matched with en
decoder_outputs = layers.Dense(input_dim, activation='sigmoid')(x)
decoder = models.Model(latent_inputs, decoder_outputs, name='decoder')

# Define VAE model.
class VAE(models.Model):
    def __init__(self, encoder, decoder, **kwargs):
        super(VAE, self).__init__(**kwargs)
        self.encoder = encoder
        self.decoder = decoder

    def call(self, inputs):
        z_mean, z_log_var, z = self.encoder(inputs)
        reconstructed = self.decoder(z)
        # Add KL divergence regularization loss.
        kl_loss = -0.5 * K.sum(1 + z_log_var - K.square(z_mean) - K.exp(z_
        kl_loss = K.mean(kl_loss)  # Ensure the KL loss is scalar.
        self.add_loss(kl_loss)
        return reconstructed
vae = VAE(encoder, decoder)
optimizer = Adam(learning_rate=1e-3)


# Compile VAE
vae = VAE(encoder, decoder)
optimizer = Adam(learning_rate=1e-3)

# Compile VAE
vae.compile(optimizer=optimizer, loss=MeanSquaredError())

# Prepare training and validation data.
X_train_np = X_train.to_numpy().astype(np.float32)
X_test_np = X_test.to_numpy().astype(np.float32)
```

```
58
59 # Ensure data is normalized if it's not already
60 X_train_np = X_train_np / np.max(X_train_np)
61 X_test_np = X_test_np / np.max(X_test_np)
62
63 # Training loop.
64 batch_size = 1000
65 epochs = 50  # Increase the number of epochs
66
67 # Add callbacks for early stopping and learning rate reduction
68 callbacks = [
69     EarlyStopping(monitor='val_loss', patience=10, verbose=1, restore_best
70     ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=5, verbose=
71 ]
72
73 # Fit the model using data.
74 history = vae.fit(
75     X_train_np, X_train_np,
76     epochs=epochs,
77     batch_size=batch_size,
78     validation_data=(X_test_np, X_test_np),
79     callbacks=callbacks
80 )
81
```

```
Epoch 1/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - loss: 0.0969 - val_loss: 7.3677
e-04 - learning_rate: 0.0010
Epoch 2/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 1.8328e-04 - val_loss: 6.
0824e-04 - learning_rate: 0.0010
Epoch 3/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 1.0208e-04 - val_loss: 5.
8690e-04 - learning_rate: 0.0010
Epoch 4/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 8.7061e-05 - val_loss: 5.
7919e-04 - learning_rate: 0.0010
Epoch 5/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 8.2661e-05 - val_loss: 5.
7548e-04 - learning_rate: 0.0010
Epoch 6/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 8.0003e-05 - val_loss: 5.
7337e-04 - learning_rate: 0.0010
Epoch 7/50
```

In [ ]:
```
1 encoder.summary()
```

Model: "encoder"

Layer (type)	Output Shape	Param #	Connected to
input_layer_2 (InputLayer)	(None, 29)	0	-
dense_8 (Dense)	(None, 64)	1,920	input_layer_2[0]…
dense_9 (Dense)	(None, 128)	8,320	dense_8[0][0]
z_mean (Dense)	(None, 2)	258	dense_9[0][0]
z_log_var (Dense)	(None, 2)	258	dense_9[0][0]
sampling (Sampling)	(None, 2)	0	z_mean[0][0], z_log_var[0][0]

Total params: 10,756 (42.02 KB)

Trainable params: 10,756 (42.02 KB)

Non-trainable params: 0 (0.00 B)

In [ ]:
```
1 decoder.summary()
```

Model: "decoder"

Layer (type)	Output Shape	Param #
z_sampling (InputLayer)	(None, 2)	0
dense_10 (Dense)	(None, 128)	384
dense_11 (Dense)	(None, 64)	8,256
dense_12 (Dense)	(None, 29)	1,885

Total params: 10,525 (41.11 KB)

Trainable params: 10,525 (41.11 KB)

Non-trainable params: 0 (0.00 B)

In [ ]:
```
1 vae.summary()
```

Model: "vae_1"

Layer (type)	Output Shape	Param #
encoder (Functional)	?	10,756
decoder (Functional)	?	10,525

Total params: 63,845 (249.40 KB)

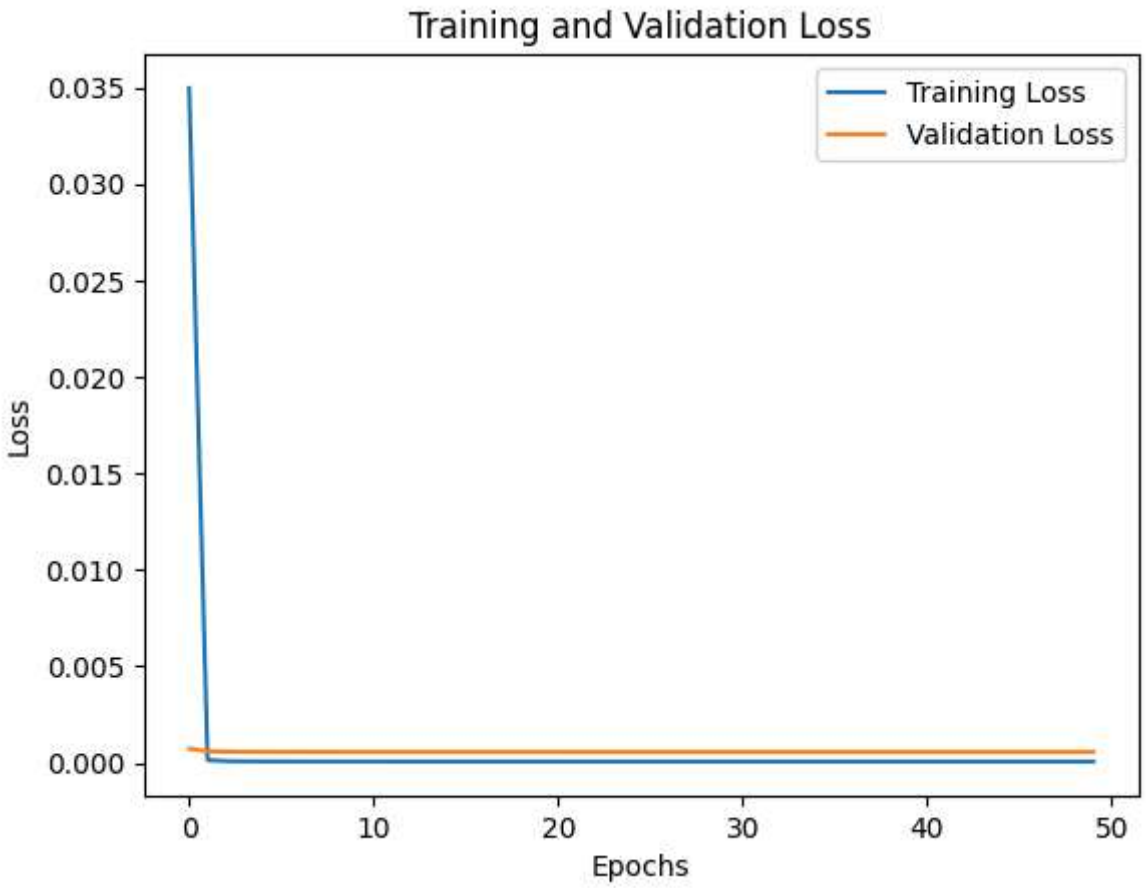
Trainable params: 21,281 (83.13 KB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 42,564 (166.27 KB)

In [ ]:

```
# Plotting training loss
plt.plot(history.history['loss'], label='Training Loss')
# Plotting validation loss
plt.plot(history.history['val_loss'], label='Validation Loss')

# Adding title and labels
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Display the plot
plt.show()

```



In [ ]:

```
def reconstruction_log_prob(eval_samples, reconstruct_samples_n):
    # Get z_mean and z_log_var from the encoder
    z_mean, z_log_var, _ = encoder(eval_samples)

    # Prepare to sample from the latent space
    epsilon = tf.random.normal(shape=(reconstruct_samples_n, z_mean.shape[
    z_samples = z_mean[tf.newaxis, :, :] + tf.exp(0.5 * z_log_var[tf.newax

    # Decode each sample
    decoded_samples = tf.map_fn(decoder, z_samples, dtype=tf.float32)  # A

    # Assuming the output of decoder is the reconstruction itself, we use
    # Here we manually compute MSE as a proxy for log_prob under a Gaussia
    mse = tf.reduce_mean(tf.square(decoded_samples - eval_samples[tf.newax
    log_prob = -mse  # Negate MSE to simulate log probability (higher is b

    return tf.reduce_mean(log_prob, axis=0)  # Average over all samples

```

Results

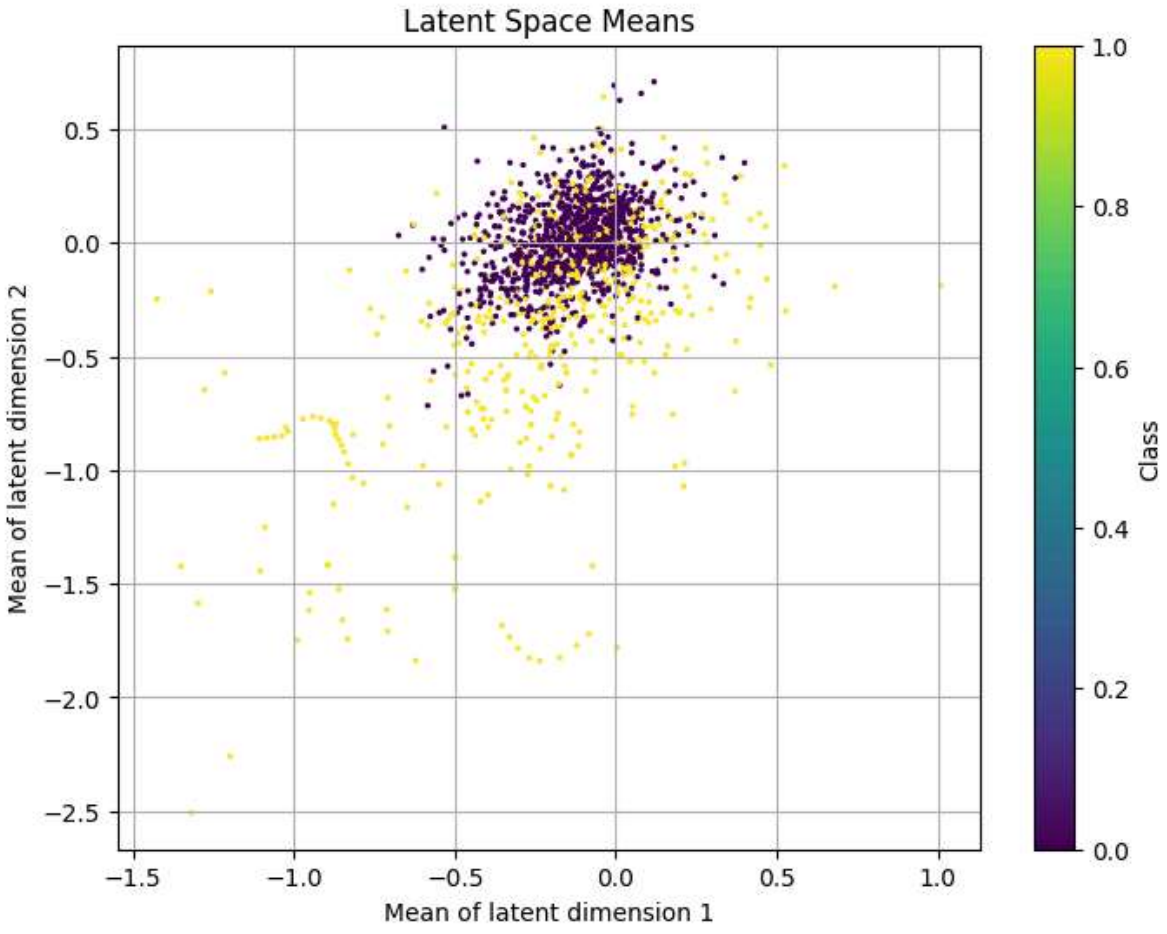
Latent space mean

This scatter plot represents data points in a two-dimensional latent space, with each point colored according to its class. The dense cluster of purple points near the center suggests a concentration of one class, while the sparser yellow points indicate another class. The plot could be showing how a model like a Variational Autoencoder separates features of different classes in its learned latent space

In [ ]:

```
# Use the encoder to get the mean, log variance, and sampled z outputs
z_mean, z_log_var, _ = encoder.predict(X)  # Use the predict method and co

# Plot these means colored by their corresponding label `Y`
plt.figure(figsize=(8, 6))
scatter = plt.scatter(z_mean[:, 0], z_mean[:, 1], c=Y, cmap='viridis', s=2
plt.colorbar(scatter, label='Class')
plt.title('Latent Space Means')
plt.xlabel('Mean of latent dimension 1')
plt.ylabel('Mean of latent dimension 2')
plt.grid(True)
plt.show()

```

```
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```

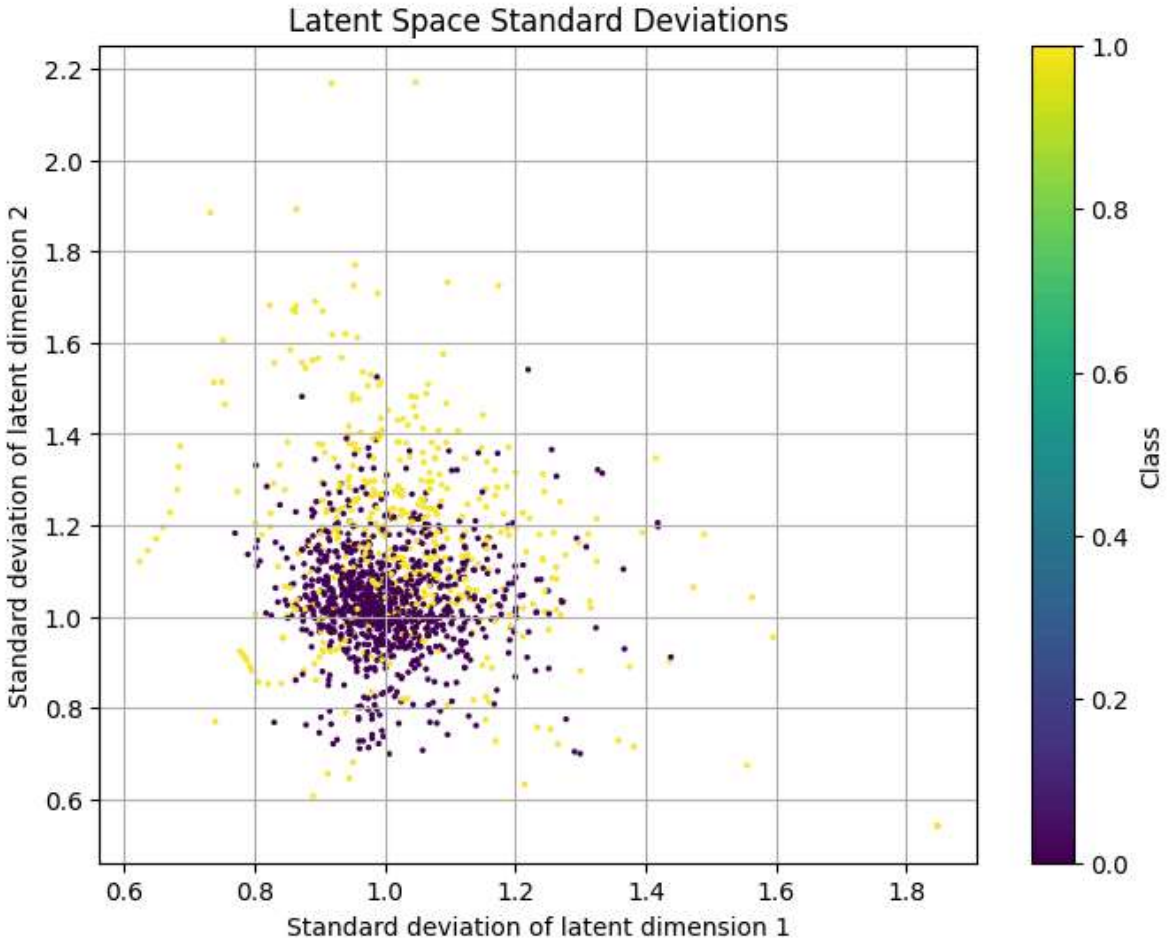


Latent space standard deviation

The scatter plot illustrates data points in terms of their standard deviation across two latent dimensions, colored by class. A cluster of purple points indicates a class with lower variability, while yellow points dispersed throughout indicate higher variability in another class. This visualization can be useful for understanding the spread and overlap of the different classes in a model's latent space

In [ ]:

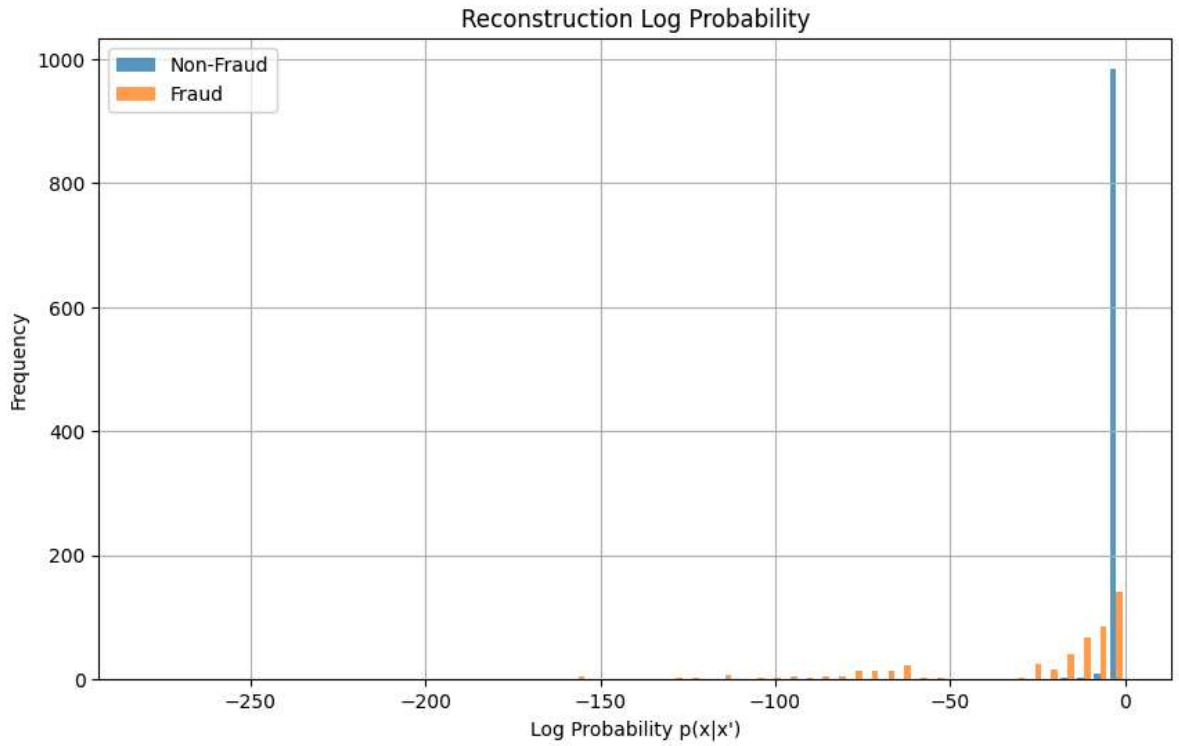
```
latent_x_std = tf.exp(0.5 * z_log_var)

plt.figure(figsize=(8, 6))
scatter = plt.scatter(latent_x_std[:, 0], latent_x_std[:, 1], c=Y, cmap='
plt.colorbar(scatter, label='Class')
plt.title('Latent Space Standard Deviations')
plt.xlabel('Standard deviation of latent dimension 1')
plt.ylabel('Standard deviation of latent dimension 2')
plt.grid(True)
plt.show()
```



Reconstruction log probability

The histogram compares the log probability of reconstruction for non-fraud and fraud transactions. Non-fraud transactions show a high frequency of high log probability scores, indicating the model reconstructs them with high likelihood. Fraud transactions, however, have a lower frequency and are spread out across lower log probability values, suggesting they are less likely to be reconstructed accurately by the model

In [ ]:
```
# Compute log probabilities
reconstruct_samples_n = 50  # Example: 100 samples
x_log_prob = reconstruction_log_prob(X, reconstruct_samples_n)

# Create a histogram of log probabilities for both classes
plt.figure(figsize=(10, 6))
plt.hist([x_log_prob[Y == 0], x_log_prob[Y == 1]], bins=60, label=['Non-Fr
plt.title('Reconstruction Log Probability')
plt.xlabel("Log Probability p(x|x')")
plt.ylabel('Frequency')
plt.legend()
plt.grid(True)
plt.show()

```



In [ ]:
```
LABELS = ["Normal", "Fraud"]
# Predict the reconstruction loss on the test set
test_predictions = vae.predict(X_test)
mse = np.mean(np.power(X_test - test_predictions, 2), axis=1)

# Create a DataFrame with true class labels and the calculated MSE
error_df = pd.DataFrame({'reconstruction_error': mse,
                         'true_class': y_test})
```

1781/1781 ━━━━━━━━━━━━━━━━━━━━ **2s** 1ms/step

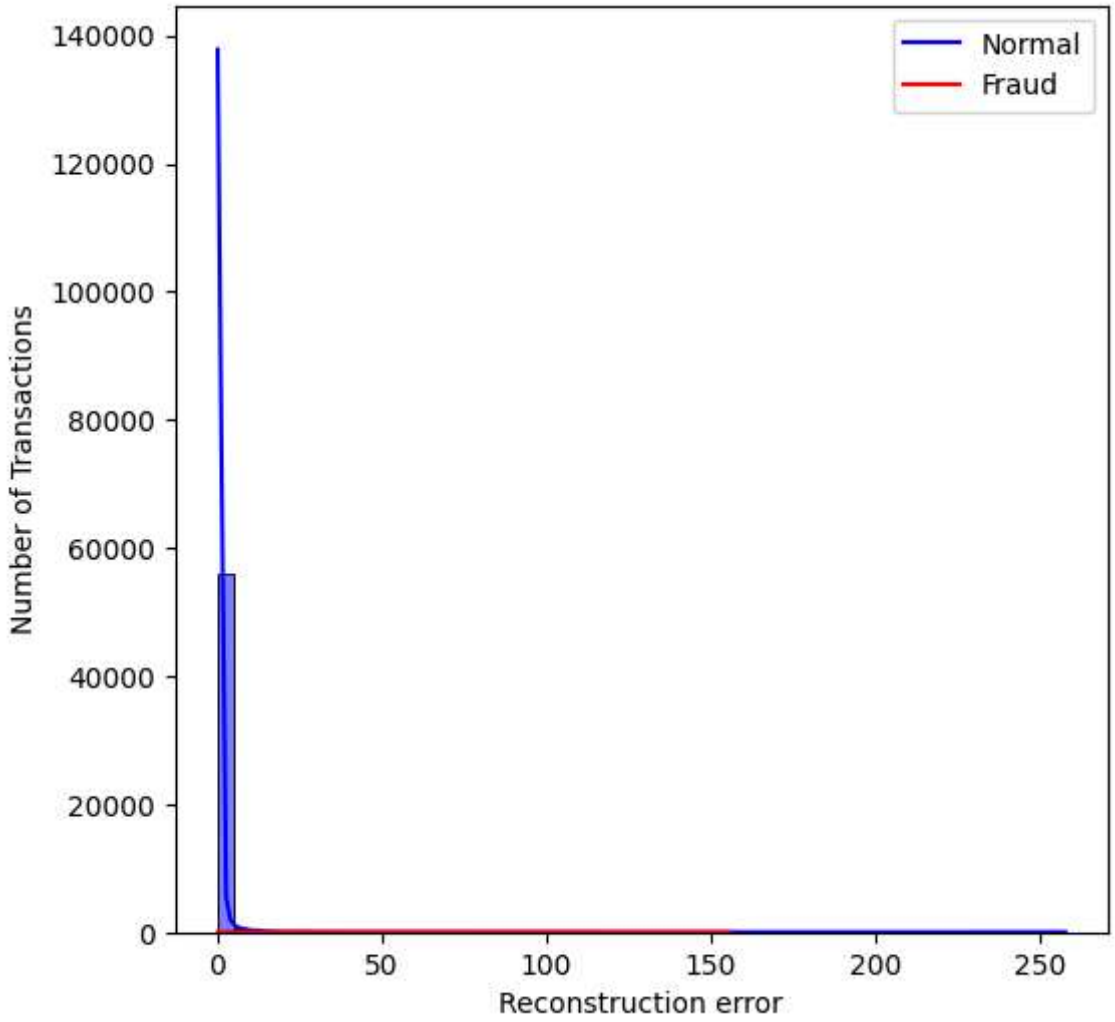
Reconstruction Error for Fraud Transactions

Normal transactions are tightly clustered around a low reconstruction error, indicating accurate model predictions. Fraud transactions are less frequent and have a wider distribution of reconstruction errors, likely due to their anomalous nature which the model finds harder to

reconstruct accurately

In [ ]:

```
# Visualizing the Reconstruction Error for different classes
fig, ax = plt.subplots(figsize=(6, 6))
normal_error_df = error_df[(error_df['true_class'] == 0)]
fraud_error_df = error_df[error_df['true_class'] == 1]

sns.histplot(normal_error_df['reconstruction_error'], bins=50, kde=True, c
sns.histplot(fraud_error_df['reconstruction_error'], bins=50, kde=True, co
plt.xlabel('Reconstruction error')
plt.ylabel('Number of Transactions')
plt.legend(['Normal', 'Fraud'])
plt.show()
```



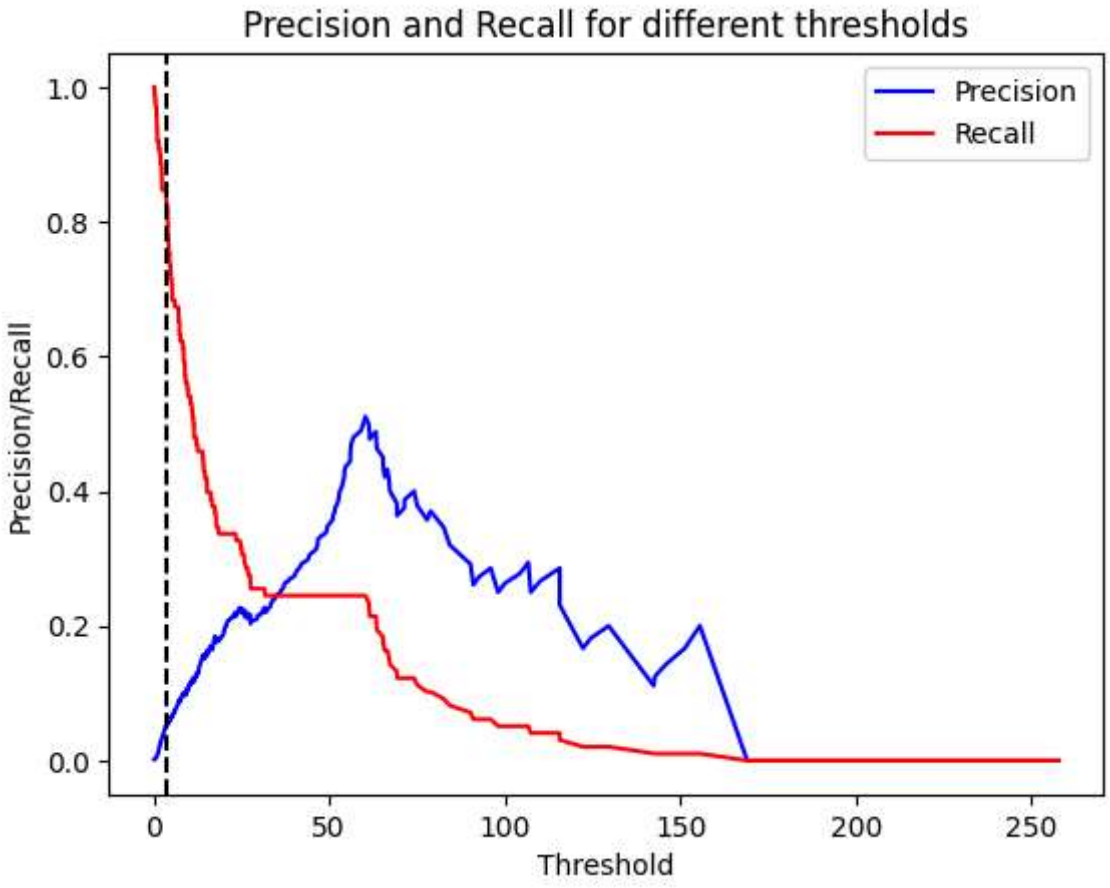
Recall vs Precision

The graph shows precision and recall values for various thresholds in a classification model. Precision starts high but quickly drops and fluctuates as the threshold increases, while recall decreases more steadily. The dashed line may represent an optimal threshold where a balance between precision and recall is achieved, often used to optimize a model's performance on both metrics.

In [ ]:

```
# Determine the optimal threshold
precision, recall, threshold = precision_recall_curve(error_df.true_class,
#threshold_f1 = threshold[np.argmax(2 * recall[:-1] * precision[:-1] / (re

threshold_f1 = 3.8

print(threshold_f1)

plt.plot(threshold, precision[:-1], 'b', label='Precision')
plt.plot(threshold, recall[:-1], 'r', label='Recall')
plt.axvline(x=threshold_f1, color='k', linestyle='--')
plt.title('Precision and Recall for different thresholds')
plt.xlabel('Threshold')
plt.ylabel('Precision/Recall')
plt.legend()
plt.show()
```

```
3.8
```

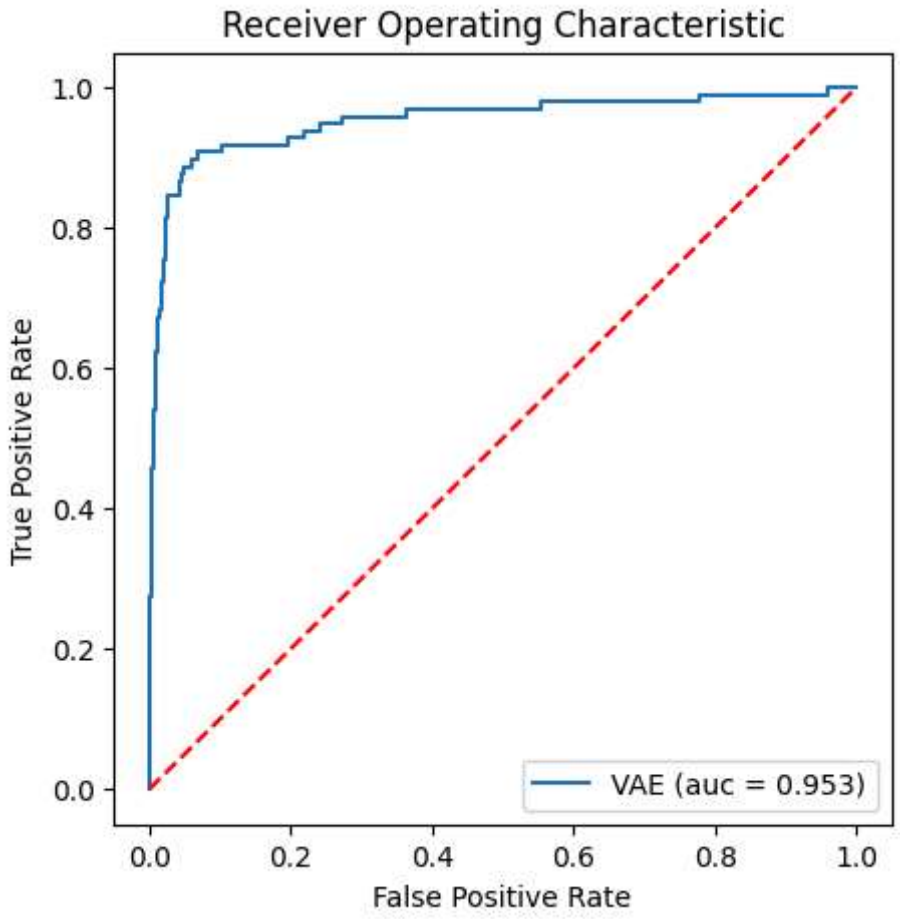


ROC curve

The ROC curve depicts the performance of a Variational Autoencoder (VAE) with an AUC of 0.953, which is quite high, indicating strong discriminative power. The curve stays close to the top-left corner, suggesting a high true positive rate with a low false positive rate, which is desirable in many classification tasks.

In [ ]:

```
# ROC Curve
fpr, tpr, thresholds = roc_curve(error_df.true_class, error_df.reconstruct
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(5, 5), dpi=100)
plt.plot(fpr, tpr, linestyle='-', label='VAE (auc = %0.3f)' % roc_auc)
plt.plot([0, 1], [0, 1], 'r--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend()
plt.show()
```

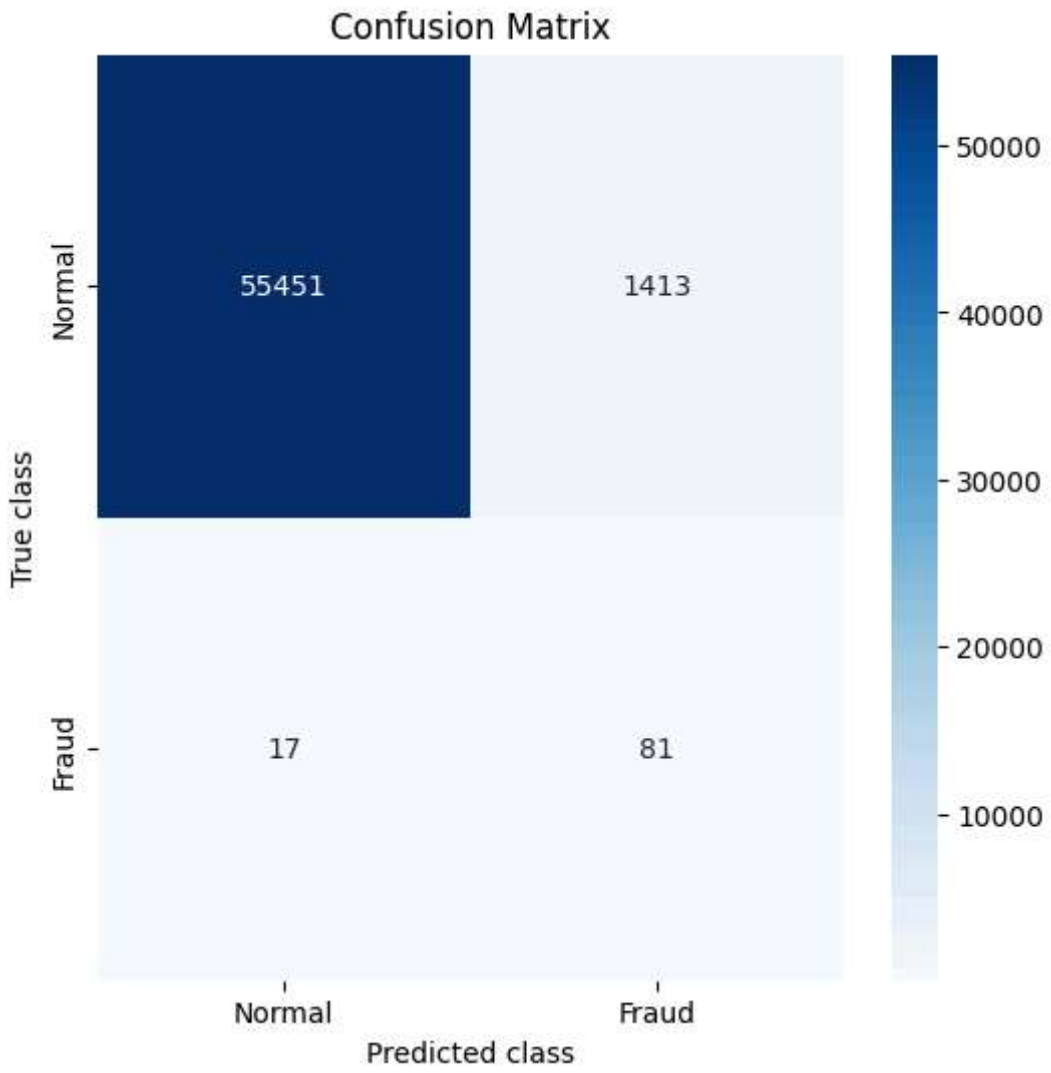


Confusion matrix

The confusion matrix shows a classifier's predictions, with 55,451 true negatives and 81 true positives, indicating correct classifications for normal and fraud cases respectively. However, there are 1,413 false positives and 17 false negatives, showing instances where the model incorrectly classified normal transactions as fraud and missed identifying some fraud transactions

In [ ]:

```
# Confusion Matrix
prediction = [1 if e > threshold_f1 else 0 for e in error_df.reconstructic
conf_matrix = confusion_matrix(error_df.true_class, prediction)

plt.figure(figsize=(6, 6))
sns.heatmap(conf_matrix, xticklabels=LABELS, yticklabels=LABELS, annot=Tru
plt.title("Confusion Matrix")
plt.ylabel('True class')
plt.xlabel('Predicted class')
plt.show()
```



In [ ]:
```
reconstructed = vae.predict(X_test_np)
reconstruction_error = np.mean(np.square(X_test_np - reconstructed), axis=

# Calculate optimal threshold and F1 score using reconstruction error
def calculate_optimal_f1(y_true, errors):
    precision, recall, thresholds = precision_recall_curve(y_true, errors)
    f1_scores = 2 * (precision * recall) / (precision + recall)
    f1_scores = np.nan_to_num(f1_scores)  # Handle potential NaNs
    max_index = np.argmax(f1_scores)
    return f1_scores[max_index], thresholds[max_index]

```

```
1781/1781 ━━━━━━━━━━━━━━━━━━━━ 1s 548us/step
```

In [ ]:
```
# Function to balance the dataset
def balance_classes(X, y):
    # Separate the classes
    class_0 = X[y == 0]
    class_1 = X[y == 1]

    # Find the smaller class size
    n_samples = min(len(class_0), len(class_1))

    # Resample classes to the size of the smaller class
    class_0_downsampled = resample(class_0, replace=False, n_samples=n_sar
    class_1_downsampled = resample(class_1, replace=False, n_samples=n_sar

    # Concatenate back to a single array
    X_balanced = np.vstack((class_0_downsampled, class_1_downsampled))
    y_balanced = np.array([0] * n_samples + [1] * n_samples)

    return X_balanced, y_balanced

# Balancing the classes in the test set
X_test_balanced, y_test_balanced = balance_classes(X_test_np, y_test)

# Prediction using the VAE
reconstructed_balanced = vae.predict(X_test_balanced)
reconstruction_error_balanced = np.mean(np.square(X_test_balanced - recons

# Calculate optimal threshold and F1 score using balanced reconstruction e
optimal_f1, optimal_threshold = calculate_optimal_f1(y_test_balanced, rec
print("Optimal Threshold:", optimal_threshold)
print("Optimal F1 Score:", optimal_f1)
```

```
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 656us/step
Optimal Threshold: 0.0007648746
Optimal F1 Score: 0.923076923076923
```