Anomaly Detection in Credit Card Transactions Using Autoencoders and Transfer Learning Models

Importing Libraries and Load Dataset

In [2]:

```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix, roc_
import time
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense
from sklearn.ensemble import IsolationForest
from sklearn.svm import OneClassSVM
```

In [3]:

```
# Load dataset
data = pd.read_csv('creditcard_data.csv')
```

In [4]:

```
# Display basic dataset information
print("Dataset Info:")
print(data.info())
print("\nDataset Head:")
print(data.head())
```

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284806 entries, 0 to 284805
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   Time    284806 non-null  float64
 1   V1      284806 non-null  float64
 2   V2      284806 non-null  float64
 3   V3      284806 non-null  float64
 4   V4      284806 non-null  float64
 5   V5      284806 non-null  float64
 6   V6      284806 non-null  float64
 7   V7      284806 non-null  float64
 8   V8      284806 non-null  float64
 9   V9      284806 non-null  float64
 10  V10     284806 non-null  float64
 11  V11     284806 non-null  float64
 12  V12     284806 non-null  float64
 13  V13     284806 non-null  float64
 14  V14     284806 non-null  float64
 15  V15     284806 non-null  float64
 16  V16     284806 non-null  float64
 17  V17     284806 non-null  float64
 18  V18     284806 non-null  float64
 19  V19     284806 non-null  float64
 20  V20     284806 non-null  float64
 21  V21     284806 non-null  float64
 22  V22     284806 non-null  float64
 23  V23     284806 non-null  float64
 24  V24     284806 non-null  float64
 25  V25     284806 non-null  float64
 26  V26     284806 non-null  float64
 27  V27     284806 non-null  float64
 28  V28     284806 non-null  float64
 29  Amount  284806 non-null  float64
 30  Class   284806 non-null  int64  
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
None

Dataset Head:
   Time        V1        V2        V3        V4        V5        V6        
V7  \
0   0.0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239
599   
1   0.0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078
803   
2   1.0 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791
461   
3   1.0 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237
609   
4   2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592
941   

         V8        V9  ...       V21       V22       V23       V24       V
25  \
0  0.098698  0.363787  ... -0.018307  0.277838 -0.110474  0.066928  0.1285
39   
1  0.085102 -0.255425  ... -0.225775 -0.638672  0.101288 -0.339846  0.1671
```

```
70
2  0.247676 -1.514654  ...  0.247998  0.771679  0.909412 -0.689281 -0.3276
42
3  0.377436 -1.387024  ... -0.108300  0.005274 -0.190321 -1.175575  0.6473
76
4 -0.270533  0.817739  ... -0.009431  0.798278 -0.137458  0.141267 -0.2060
10

        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]
```

In [5]:

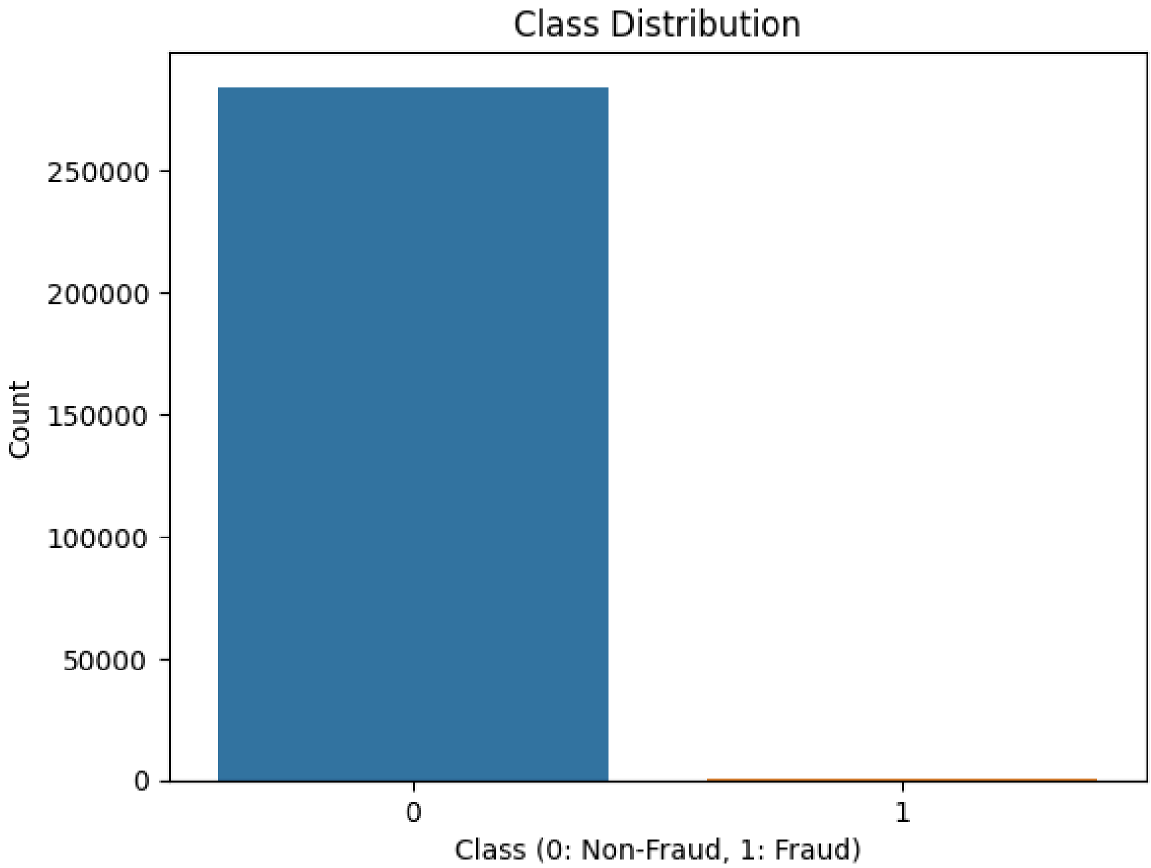
```
# Check for class imbalance
print("\nClass Distribution:")
print(data['Class'].value_counts())
```

```
Class Distribution:
Class
0    284314
1       492
Name: count, dtype: int64
```

Exploratory Data Analysis

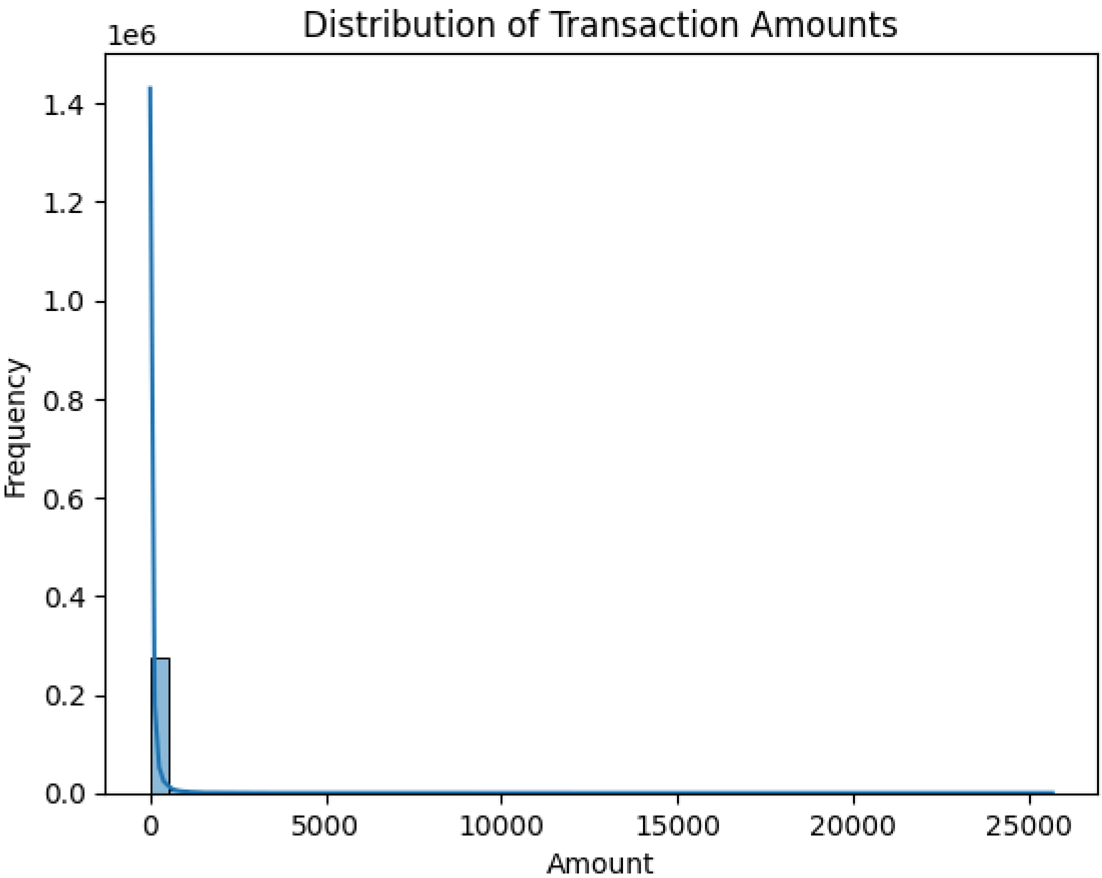
In [6]:

```
# Distribution of Class
sns.countplot(x='Class', data=data)
plt.title('Class Distribution')
plt.xlabel('Class (0: Non-Fraud, 1: Fraud)')
plt.ylabel('Count')
plt.show()
```



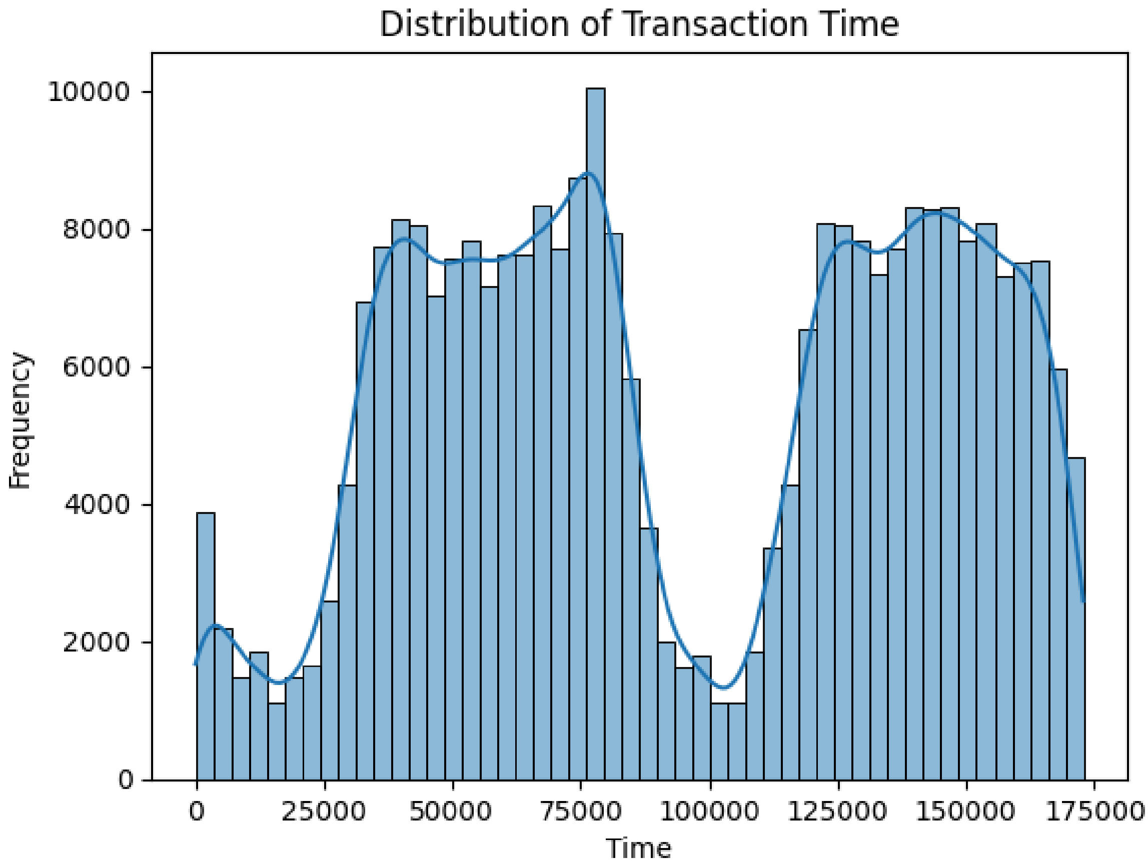
In [7]:
```
# Distribution of 'Amount'
sns.histplot(data['Amount'], bins=50, kde=True)
plt.title('Distribution of Transaction Amounts')
plt.xlabel('Amount')
plt.ylabel('Frequency')
plt.show()
```

```
/home/saky/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:111
9: FutureWarning: use_inf_as_na option is deprecated and will be removed i
n a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```

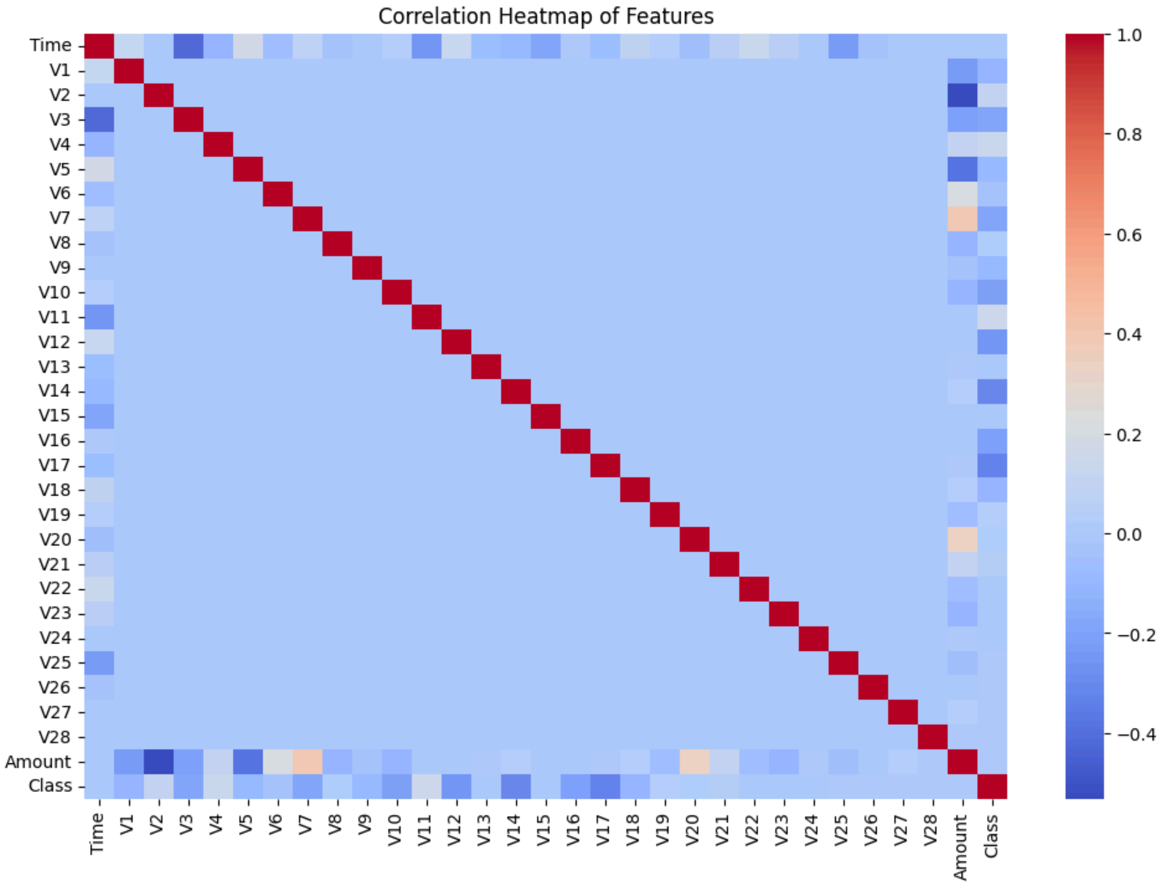


In [8]:
```python
# Distribution of 'Time'
sns.histplot(data['Time'], bins=50, kde=True)
plt.title('Distribution of Transaction Time')
plt.xlabel('Time')
plt.ylabel('Frequency')
plt.show()
```

```
/home/saky/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:111
9: FutureWarning: use_inf_as_na option is deprecated and will be removed i
n a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



In [9]:
```
# Correlation Heatmap
plt.figure(figsize=(12, 8))
corr = data.corr()
sns.heatmap(corr, cmap='coolwarm', annot=False, cbar=True)
plt.title('Correlation Heatmap of Features')
plt.show()
```



Pre-processing

In [10]:
```
# Check for missing values
print("\nMissing Values:")
print(data.isnull().sum())
```

```
Missing Values:
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

In [11]:
```
# Feature scaling for 'Amount' and 'Time'
scaler = StandardScaler()
data[['Time', 'Amount']] = scaler.fit_transform(data[['Time', 'Amount']])
```

In [12]:
```
# Features and target
X = data.drop('Class', axis=1)
y = data['Class']
```

In [13]:
```
# PCA for dimensionality reduction (optional)
pca = PCA(n_components=15)
X_reduced = pca.fit_transform(X)
print(f"\nExplained Variance Ratio by PCA: {pca.explained_variance_ratio_
```

```
Explained Variance Ratio by PCA: [0.12088216 0.09654339 0.07924925 0.06548
464 0.06090455 0.0549235
 0.04985609 0.04372533 0.03692044 0.03686605 0.03580735 0.0307752
 0.03029738 0.02844008 0.02659217]
```

In [15]:
```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X_reduced, y, test_si
```

In [16]:
```
# Use only normal transactions for training the autoencoder
X_train_normal = X_train[y_train == 0]
```

Autoencoder Design and Training

In [22]:
```
# Autoencoder architecture
input_dim = X_train_normal.shape[1]  # Number of features
encoding_dim = 8  # Bottleneck layer dimension
```

In [23]:
```
# Define the Autoencoder model
input_layer = Input(shape=(input_dim,))
encoded = Dense(16, activation='relu')(input_layer)
encoded = Dense(encoding_dim, activation='relu')(encoded)
decoded = Dense(16, activation='relu')(encoded)
decoded = Dense(input_dim, activation='sigmoid')(decoded)

autoencoder = Model(inputs=input_layer, outputs=decoded)
autoencoder.compile(optimizer='adam', loss='mse')
```

```
2024-11-25 17:27:27.177670: E external/local_xla/xla/stream_executor/cuda/
cuda_driver.cc:152] failed call to cuInit: INTERNAL: CUDA error: Failed ca
ll to cuInit: UNKNOWN ERROR (303)
```

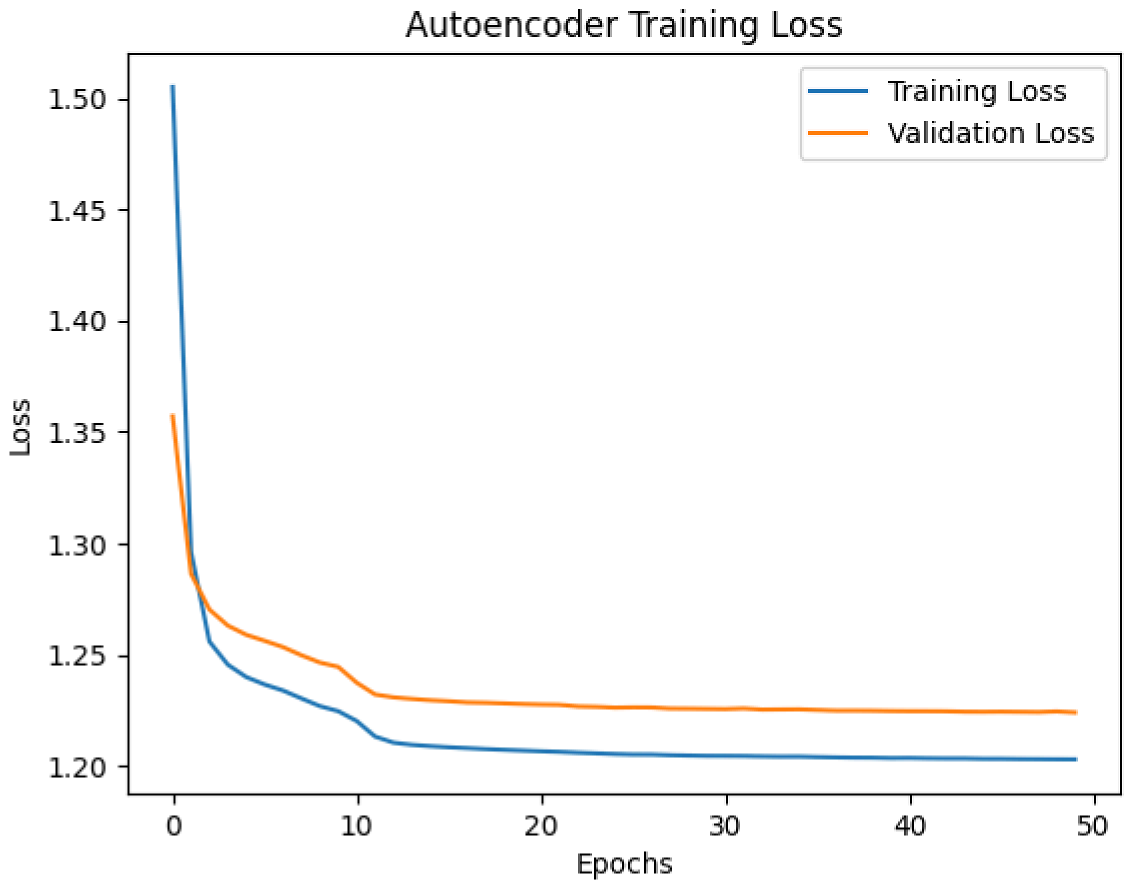
In [24]:
```
# Train the autoencoder
start_time = time.time()
history = autoencoder.fit(
    X_train_normal,
    X_train_normal,
    epochs=50,
    batch_size=256,
    validation_split=0.2,
    shuffle=True,
    verbose=1
)
end_time = time.time()

print(f"\nAutoencoder Training Time: {end_time - start_time:.2f} seconds"
```

```
Epoch 1/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 1.6485 - val_loss: 1.3570
Epoch 2/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 1.3327 - val_loss: 1.2863
Epoch 3/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 1.2436 - val_loss: 1.2703
Epoch 4/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 1.2955 - val_loss: 1.2630
Epoch 5/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2814 - val_loss: 1.2589
Epoch 6/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2542 - val_loss: 1.2562
Epoch 7/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.3370 - val_loss: 1.2534
Epoch 8/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2090 - val_loss: 1.2497
Epoch 9/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2305 - val_loss: 1.2464
Epoch 10/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2376 - val_loss: 1.2445
Epoch 11/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2044 - val_loss: 1.2374
Epoch 12/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2088 - val_loss: 1.2321
Epoch 13/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1940 - val_loss: 1.2308
Epoch 14/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2253 - val_loss: 1.2301
Epoch 15/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1817 - val_loss: 1.2295
Epoch 16/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2215 - val_loss: 1.2290
Epoch 17/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2176 - val_loss: 1.2285
Epoch 18/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2266 - val_loss: 1.2283
Epoch 19/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2094 - val_loss: 1.2281
Epoch 20/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1944 - val_loss: 1.2278
Epoch 21/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1869 - val_loss: 1.2276
Epoch 22/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1717 - val_loss: 1.2274
Epoch 23/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1957 - val_loss: 1.2267
Epoch 24/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2052 - val_loss: 1.2265
Epoch 25/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1907 - val_loss: 1.2262
Epoch 26/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1804 - val_loss: 1.2263
Epoch 27/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1779 - val_loss: 1.2262
Epoch 28/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1972 - val_loss: 1.2257
Epoch 29/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2168 - val_loss: 1.2257
Epoch 30/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1898 - val_loss: 1.2256
```

```
Epoch 31/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2035 - val_loss: 1.2255
Epoch 32/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1789 - val_loss: 1.2258
Epoch 33/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1953 - val_loss: 1.2253
Epoch 34/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2010 - val_loss: 1.2253
Epoch 35/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1633 - val_loss: 1.2254
Epoch 36/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1982 - val_loss: 1.2251
Epoch 37/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2274 - val_loss: 1.2248
Epoch 38/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2089 - val_loss: 1.2248
Epoch 39/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1904 - val_loss: 1.2248
Epoch 40/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1976 - val_loss: 1.2246
Epoch 41/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1858 - val_loss: 1.2246
Epoch 42/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2016 - val_loss: 1.2245
Epoch 43/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2097 - val_loss: 1.2245
Epoch 44/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1698 - val_loss: 1.2243
Epoch 45/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 1.1947 - val_loss: 1.2243
Epoch 46/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 1.2275 - val_loss: 1.2243
Epoch 47/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 1.1890 - val_loss: 1.2242
Epoch 48/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1947 - val_loss: 1.2242
Epoch 49/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.2162 - val_loss: 1.2244
Epoch 50/50
711/711 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 1.1886 - val_loss: 1.2240

Autoencoder Training Time: 49.95 seconds
```

In [25]:

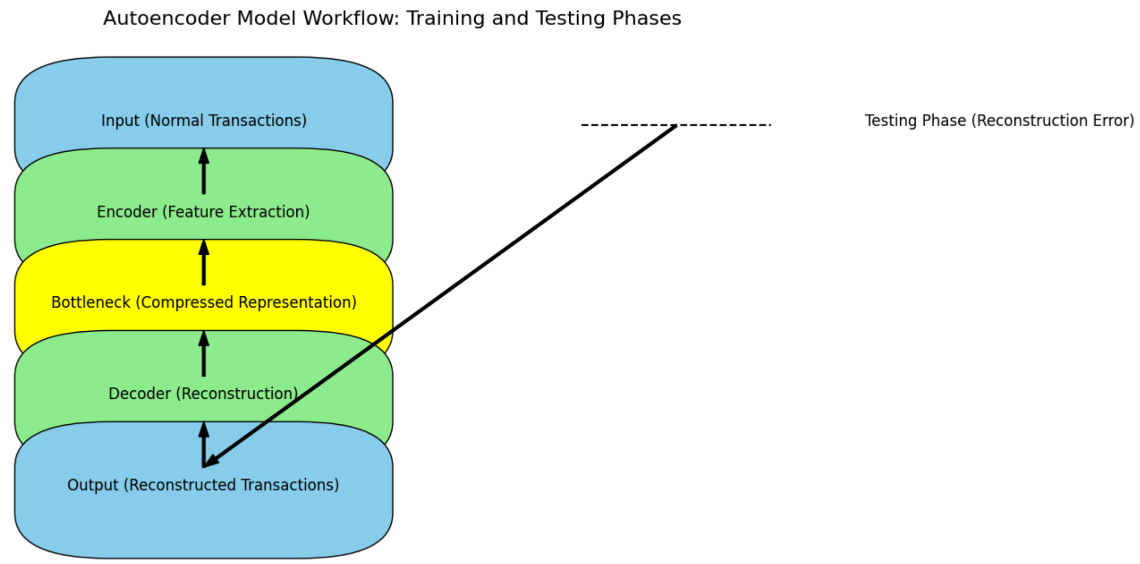
```python
# Plot training loss
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Autoencoder Training Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



Autoencoder Model Workflow

In [4]:
```
# Importing the necessary Libraries
import matplotlib.pyplot as plt
import matplotlib.patches as patches

# Defining the function
def plot_autoencoder_workflow():
    # Create a figure and axis for the diagram
    fig, ax = plt.subplots(figsize=(12, 8))

    # Set the background color
    ax.set_facecolor('white')

    # Remove axes for a cleaner look
    ax.axis('off')

    # Draw the input layer box
    ax.add_patch(patches.FancyBboxPatch((0.1, 0.7), 0.2, 0.1, boxstyle="r
    ax.text(0.2, 0.75, 'Input (Normal Transactions)', horizontalalignment

    # Draw the encoder layers
    ax.add_patch(patches.FancyBboxPatch((0.1, 0.5), 0.2, 0.1, boxstyle="r
    ax.text(0.2, 0.55, 'Encoder (Feature Extraction)', horizontalalignmen

    # Draw the bottleneck layer
    ax.add_patch(patches.FancyBboxPatch((0.1, 0.3), 0.2, 0.1, boxstyle="r
    ax.text(0.2, 0.35, 'Bottleneck (Compressed Representation)', horizont

    # Draw the decoder layers
    ax.add_patch(patches.FancyBboxPatch((0.1, 0.1), 0.2, 0.1, boxstyle="r
```

```
    ax.text(0.2, 0.15, 'Decoder (Reconstruction)', horizontalalignment='c

    # Draw the output layer
    ax.add_patch(patches.FancyBboxPatch((0.1, -0.1), 0.2, 0.1, boxstyle="
    ax.text(0.2, -0.05, 'Output (Reconstructed Transactions)', horizontal

    # Arrow from Input to Encoder
    ax.annotate('', xy=(0.2, 0.7), xytext=(0.2, 0.6),
                arrowprops=dict(facecolor='black', shrinkA=5, shrinkB=5,

    # Arrow from Encoder to Bottleneck
    ax.annotate('', xy=(0.2, 0.5), xytext=(0.2, 0.4),
                arrowprops=dict(facecolor='black', shrinkA=5, shrinkB=5,

    # Arrow from Bottleneck to Decoder
    ax.annotate('', xy=(0.2, 0.3), xytext=(0.2, 0.2),
                arrowprops=dict(facecolor='black', shrinkA=5, shrinkB=5,

    # Arrow from Decoder to Output
    ax.annotate('', xy=(0.2, 0.1), xytext=(0.2, 0),
                arrowprops=dict(facecolor='black', shrinkA=5, shrinkB=5,

    # Draw a dashed line for testing phase (reconstruction error calculat
    ax.plot([0.6, 0.8], [0.75, 0.75], 'k--')  # Horizontal dashed line
    ax.text(0.9, 0.75, 'Testing Phase (Reconstruction Error)', horizontal

    # Arrow from Output to Testing Phase
    ax.annotate('', xy=(0.2, 0), xytext=(0.7, 0.75),
                arrowprops=dict(facecolor='black', shrinkA=5, shrinkB=5,

    plt.title('Autoencoder Model Workflow: Training and Testing Phases',
    plt.show()

# Call the function to plot the diagram
plot_autoencoder_workflow()
```



Anomaly Detection with Autoencoder

In [26]:
```
# Reconstruction error on test data
X_test_reconstructed = autoencoder.predict(X_test)
```

```
reconstruction_error = np.mean(np.square(X_test - X_test_reconstructed),
```

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

In [27]:
```
# Determine threshold for anomaly detection
threshold = np.percentile(reconstruction_error[y_test == 0], 95)
print(f"\nReconstruction Error Threshold: {threshold}")
```

```
Reconstruction Error Threshold: 2.5196568404932487
```

In [28]:
```
# Predict anomalies
y_pred_auto = (reconstruction_error > threshold).astype(int)
```

In [29]:
```
# Evaluate Autoencoder
print("\nAutoencoder Metrics:")
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_auto))
print("\nClassification Report:\n", classification_report(y_test, y_pred_
print("\nROC AUC Score:", roc_auc_score(y_test, reconstruction_error))
```

```
Autoencoder Metrics:
Confusion Matrix:
 [[54020  2844]
 [   14    84]]

Classification Report:
               precision    recall  f1-score   support

           0       1.00      0.95      0.97     56864
           1       0.03      0.86      0.06        98

    accuracy                           0.95     56962
   macro avg       0.51      0.90      0.51     56962
weighted avg       1.00      0.95      0.97     56962


ROC AUC Score: 0.943027330515774
```

Transfer Learning Models

Isolation Forest

In [30]:
```
# Train Isolation Forest
iso_forest = IsolationForest(contamination=0.01, random_state=42)
start_time = time.time()
iso_forest.fit(X_train)
end_time = time.time()

print(f"\nIsolation Forest Training Time: {end_time - start_time:.2f} sec
```

```
Isolation Forest Training Time: 1.49 seconds
```

In [31]:
```
# Predict anomalies
y_pred_iso = iso_forest.predict(X_test)
y_pred_iso = [1 if x == -1 else 0 for x in y_pred_iso]
```

In [32]:
```
# Evaluate Isolation Forest
print("\nIsolation Forest Metrics:")
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_iso))
```

```
print("\nClassification Report:\n", classification_report(y_test, y_pred_
print("\nROC AUC Score:", roc_auc_score(y_test, iso_forest.decision_funct
```

```
Isolation Forest Metrics:
Confusion Matrix:
 [[56322   542]
 [   33    65]]

Classification Report:
               precision    recall  f1-score   support

           0       1.00      0.99      0.99     56864
           1       0.11      0.66      0.18        98

    accuracy                           0.99     56962
   macro avg       0.55      0.83      0.59     56962
weighted avg       1.00      0.99      0.99     56962


ROC AUC Score: 0.049153978558221255
```

One-class SVM

In [33]:
```
# Train One-Class SVM
svm_model = OneClassSVM(kernel='rbf', nu=0.01, gamma=0.1)
start_time = time.time()
svm_model.fit(X_train_normal)
end_time = time.time()

print(f"\nOne-Class SVM Training Time: {end_time - start_time:.2f} second
```

```
One-Class SVM Training Time: 339.17 seconds
```

In [34]:
```
# Predict anomalies
y_pred_svm = svm_model.predict(X_test)
y_pred_svm = [1 if x == -1 else 0 for x in y_pred_svm]
```

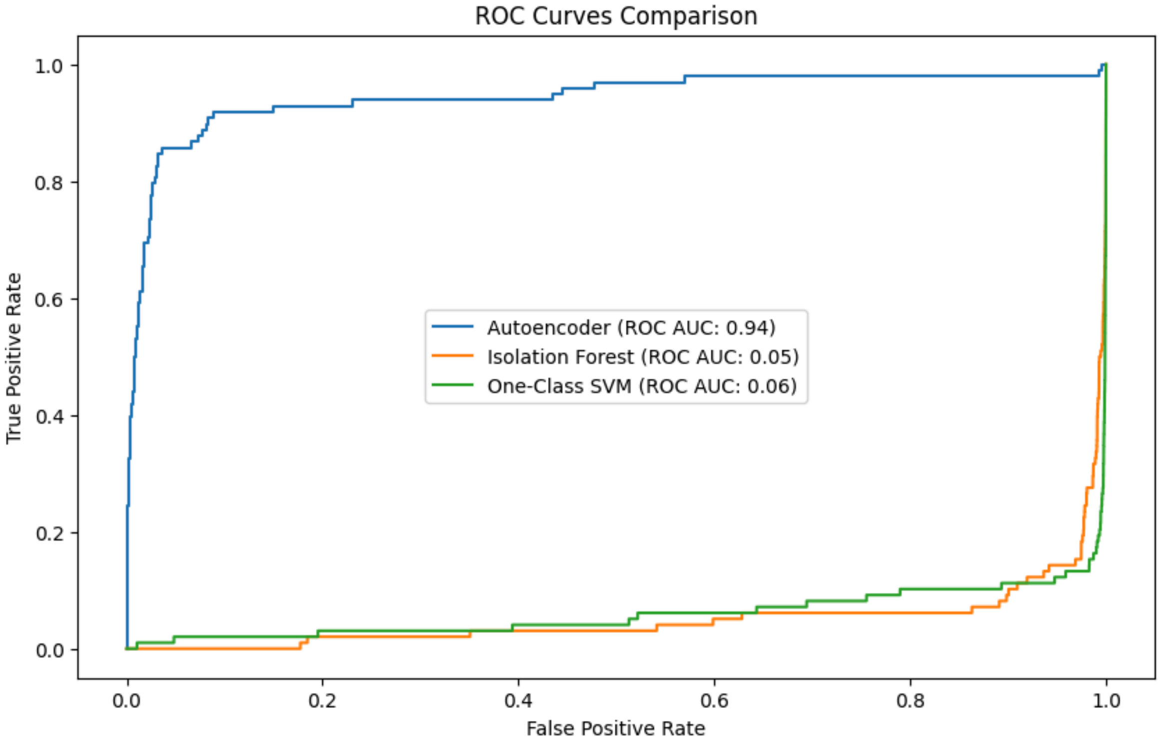
In [35]:
```
# Evaluate One-Class SVM
print("\nOne-Class SVM Metrics:")
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_svm))
print("\nClassification Report:\n", classification_report(y_test, y_pred_
print("\nROC AUC Score:", roc_auc_score(y_test, svm_model.decision_functi
```

```
One-Class SVM Metrics:
Confusion Matrix:
 [[55509  1355]
 [   13    85]]

Classification Report:
               precision    recall  f1-score   support

           0       1.00      0.98      0.99     56864
           1       0.06      0.87      0.11        98

    accuracy                           0.98     56962
   macro avg       0.53      0.92      0.55     56962
weighted avg       1.00      0.98      0.99     56962


ROC AUC Score: 0.05924455988078968
```

Visualization and Comparison

In [36]:
```
# Compare ROC Curves
fpr_auto, tpr_auto, _ = roc_curve(y_test, reconstruction_error)
fpr_iso, tpr_iso, _ = roc_curve(y_test, iso_forest.decision_function(X_te
fpr_svm, tpr_svm, _ = roc_curve(y_test, svm_model.decision_function(X_tes
```

In [37]:
```
plt.figure(figsize=(10, 6))
plt.plot(fpr_auto, tpr_auto, label='Autoencoder (ROC AUC: {:.2f})'.format
plt.plot(fpr_iso, tpr_iso, label='Isolation Forest (ROC AUC: {:.2f})'.for
plt.plot(fpr_svm, tpr_svm, label='One-Class SVM (ROC AUC: {:.2f})'.format
plt.title('ROC Curves Comparison')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```



Thank You!

Thanks for your patience and understanding! 💖