Analysis of Credit Card Fraud Detection Using Deep Learning Techniques

Research Context and Motivation Creditcardfraudrepresents a critical challenge in financial security, causing billions in annual losses globally. This research addresses the urgent need for sophisticated, adaptive fraud detection methodologies leveraging cutting-edge machine learning approaches.

Fraud detection often employs classification techniques, approaching the issue as a binary classification task. In this context, each transaction is classified as either fraudulent (1) or non-fraudulent (0). This method is most effective when applied to a balanced dataset.

However, in real-world scenarios, datasets are rarely balanced, as fraudulent transactions represent only a small fraction of the overall data. To address this, synthetic fraudulent data is often generated to balance the dataset.

Given the inherent imbalance in real-world datasets and the fortunate rarity of fraudulent transactions, anomaly detection becomes a highly effective alternative. This approach identifies fraud cases by treating them as anomalies or outliers within the dataset. Anomaly detection is particularly valuable when fraudulent transactions are exceedingly rare.

By utilizing advanced deep learning techniques such as autoencoders, Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, or Generative Adversarial Networks (GANs), the model can learn the normal patterns of non-fraudulent transactions. Deviations from these learned patterns are then flagged as potential frauds, enabling more accurate and efficient detection of fraudulent activities.

Table of Content

Main Objective

Evaluate deep learning models' performance in detecting fraudulent credit card transactions using LSTM, RNN, and Autoencoder techniques to enhance fraud prevention strategies.

Dataset Overview

Quantitative Characteristics

- Total Transactions: 284,807
- Fraudulent Transactions: 492 (0.172% of total)
- Timespan: Two consecutive days in September 2013
- Geographical Scope: European cardholders

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plot_utils as pu

# Load the dataset
url = 'creditcard.csv'
ccds = pd.read_csv(url)
```

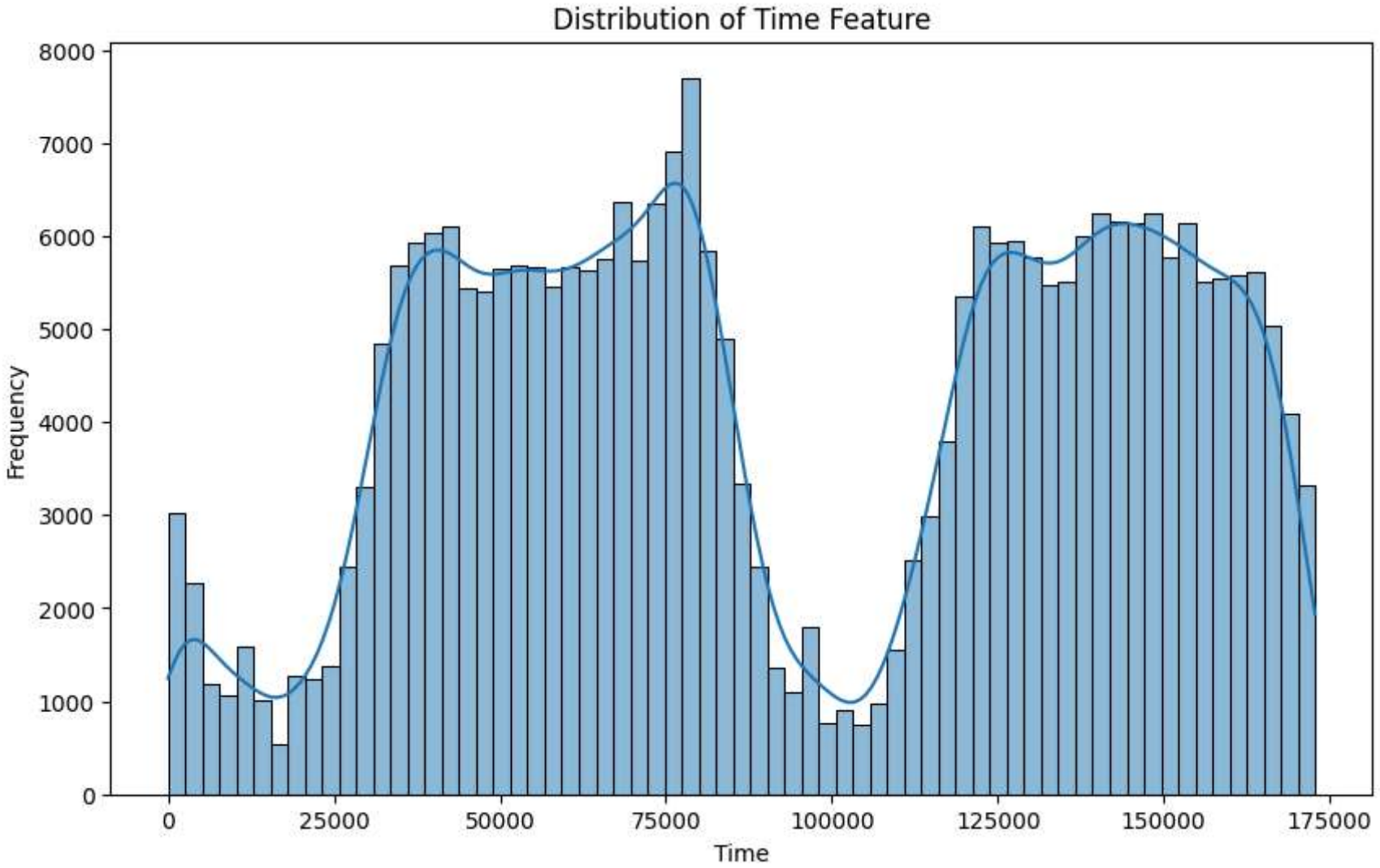
```
# Display basic information about the dataset
print(ccds.info())
# Display summary statistics
print(ccds.describe())
# Check for missing values
print(ccds.isnull().sum())
```

```
<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
None
                Time            V1            V2            V3            V4  \
count  284807.000000  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05   
```

```
mean    94813.859575  1.168375e-15  3.416908e-16 -1.379537e-15  2.074095e-15
std     47488.145955  1.958696e+00  1.651309e+00  1.516255e+00  1.415869e+00
min         0.000000 -5.640751e+01 -7.271573e+01 -4.832559e+01 -5.683171e+00
25%     54201.500000 -9.203734e-01 -5.985499e-01 -8.903648e-01 -8.486401e-01
50%     84692.000000  1.810880e-02  6.548556e-02  1.798463e-01 -1.984653e-02
75%    139320.500000  1.315642e+00  8.037239e-01  1.027196e+00  7.433413e-01
max    172792.000000  2.454930e+00  2.205773e+01  9.382558e+00  1.687534e+01

                V5            V6            V7            V8            V9  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean   9.604066e-16  1.487313e-15 -5.556467e-16  1.213481e-16 -2.406331e-15
std    1.380247e+00  1.332271e+00  1.237094e+00  1.194353e+00  1.098632e+00
min   -1.137433e+02 -2.616051e+01 -4.355724e+01 -7.321672e+01 -1.343407e+01
25%   -6.915971e-01 -7.682956e-01 -5.540759e-01 -2.086297e-01 -6.430976e-01
50%   -5.433583e-02 -2.741871e-01  4.010308e-02  2.235804e-02 -5.142873e-02
75%    6.119264e-01  3.985649e-01  5.704361e-01  3.273459e-01  5.971390e-01
max    3.480167e+01  7.330163e+01  1.205895e+02  2.000721e+01  1.559499e+01

       ...           V21           V22           V23           V24  \
count  ...  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean   ...  1.654067e-16 -3.568593e-16  2.578648e-16  4.473266e-15
std    ...  7.345240e-01  7.257016e-01  6.244603e-01  6.056471e-01
min    ... -3.483038e+01 -1.093314e+01 -4.480774e+01 -2.836627e+00
25%    ... -2.283949e-01 -5.423504e-01 -1.618463e-01 -3.545861e-01
50%    ... -2.945017e-02  6.781943e-03 -1.119293e-02  4.097606e-02
75%    ...  1.863772e-01  5.285536e-01  1.476421e-01  4.395266e-01
max    ...  2.720284e+01  1.050309e+01  2.252841e+01  4.584549e+00

                V25           V26           V27           V28         Amount  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  284807.000000
mean   5.340915e-16  1.683437e-15 -3.660091e-16 -1.227390e-16      88.349619
std    5.212781e-01  4.822270e-01  4.036325e-01  3.300833e-01     250.120109
min   -1.029540e+01 -2.604551e+00 -2.256568e+01 -1.543008e+01       0.000000
25%   -3.171451e-01 -3.269839e-01 -7.083953e-02 -5.295979e-02       5.600000
50%    1.659350e-02 -5.213911e-02  1.342146e-03  1.124383e-02      22.000000
75%    3.507156e-01  2.409522e-01  9.104512e-02  7.827995e-02      77.165000
max    7.519589e+00  3.517346e+00  3.161220e+01  3.384781e+01   25691.160000

              Class
count  284807.000000
mean        0.001727
```

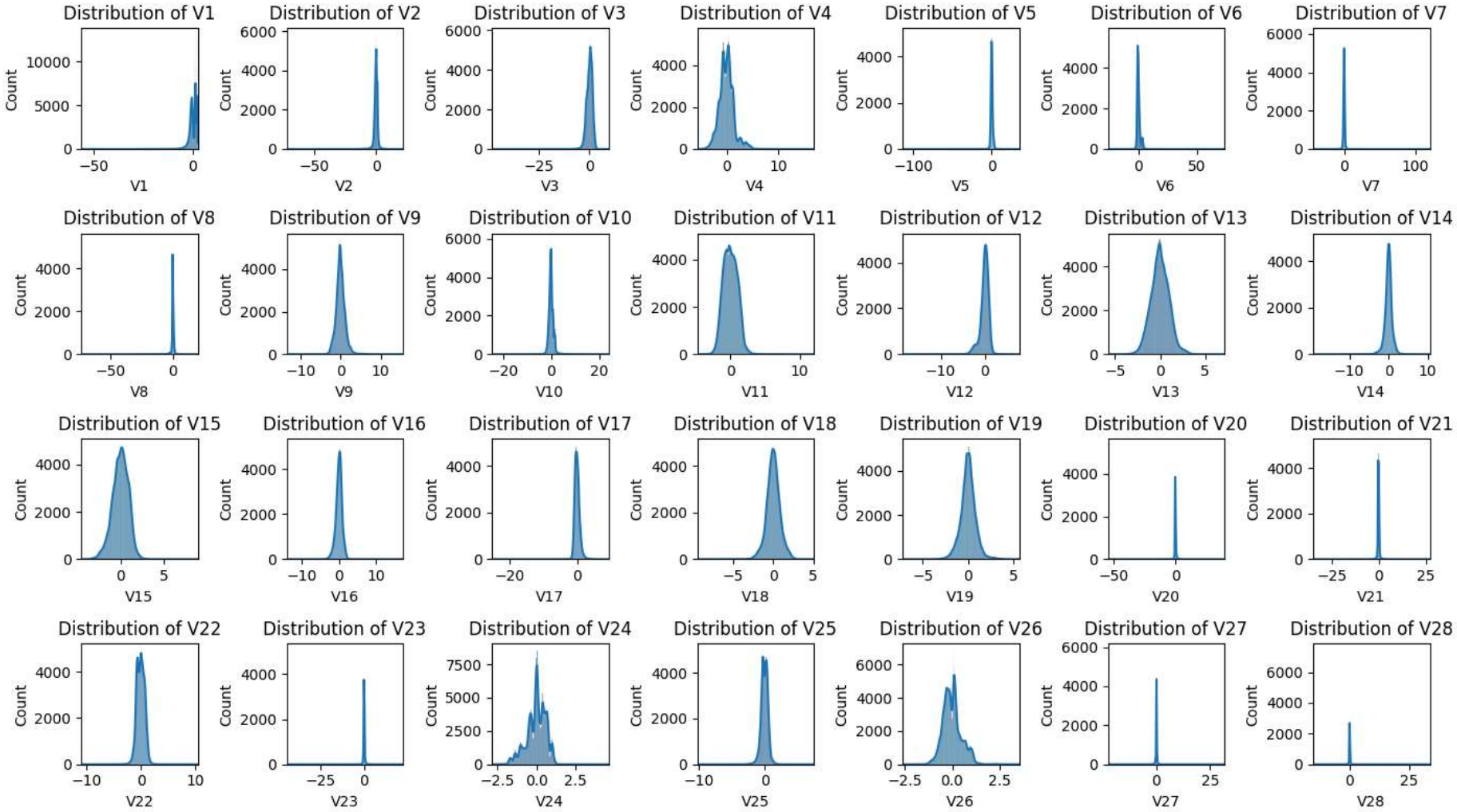
```
std       0.041527
min       0.000000
25%       0.000000
50%       0.000000
75%       0.000000
max       1.000000

[8 rows x 31 columns]
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 [2]:
```
# Plot the 'Time' feature
pu.plot_time(ccds)
```



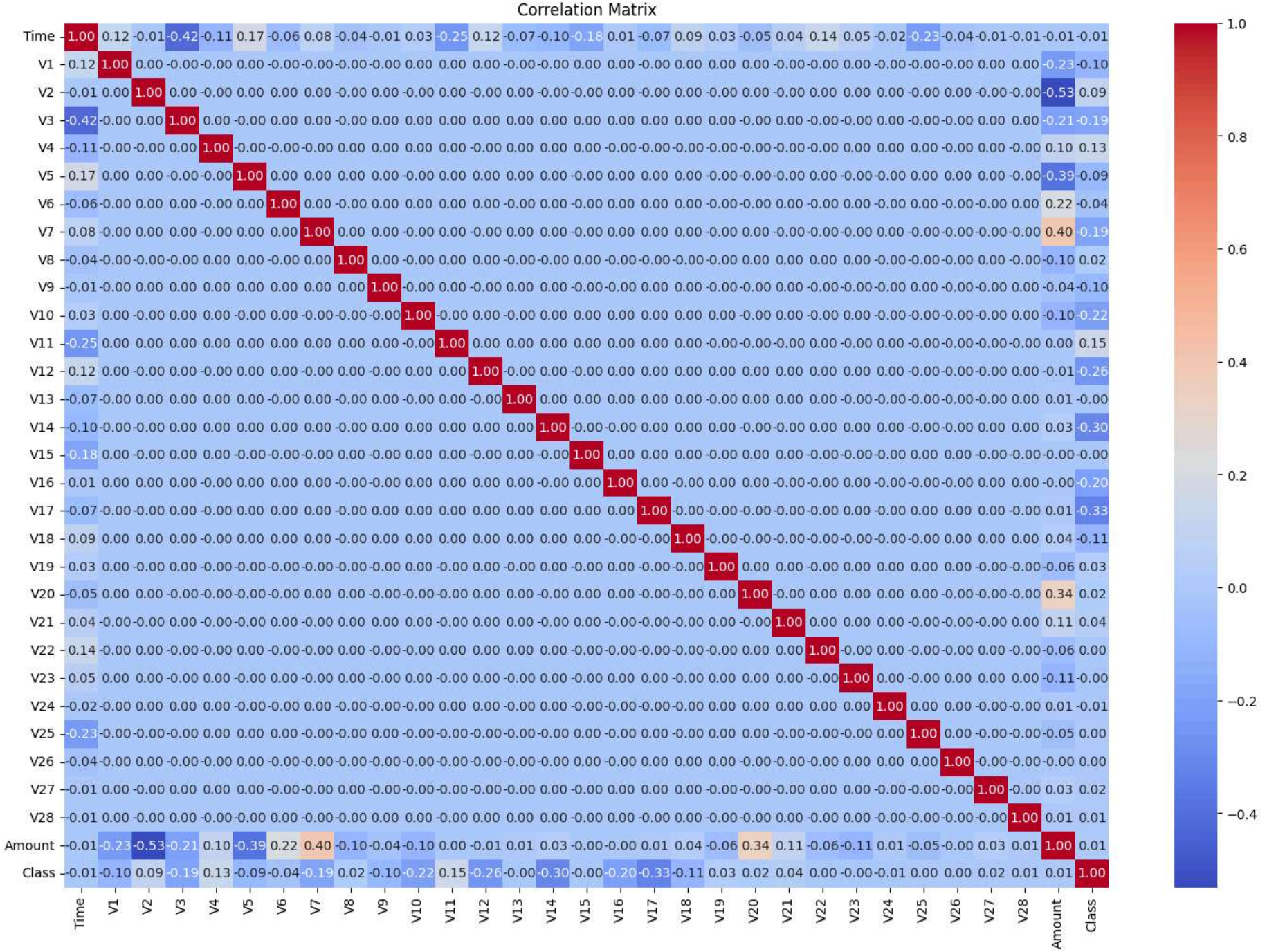
In [15]:
```
# Plot the anonymized Features V1 to V28
# Features V1 to V28
anonymized_features = [f"V{i}" for i in range(1, 29)]
```

```python
# Create subplots
fig, axes = plt.subplots(nrows=4, ncols=7, figsize=(14, 8), tight_layout=True)
axes = axes.flatten()

# Plot distribution for each feature
for i, feature in enumerate(anonymized_features):
    sns.histplot(ccds[feature], kde=True, ax=axes[i], color='#1f77b4')
    axes[i].set_title(f'Distribution of {feature}')
    axes[i].set_xlim([ccds[feature].min(), ccds[feature].max()])

# Remove any empty subplots
for j in range(len(anonymized_features), len(axes)):
    fig.delaxes(axes[j])

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



In [4]:
```
#Correlation MAtrix
plt.figure(figsize=(18, 12))
correlation_matrix = ccds.corr()
# Format the annotations to 2 decimal places, for better representation
formatted_corr_matrix = correlation_matrix.applymap(lambda x: round(x, 2))
sns.heatmap(correlation_matrix, annot=formatted_corr_matrix, fmt='.2f', cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```

```
C:\Users\carlo\AppData\Local\Temp\ipykernel_10120\1050167756.py:5: FutureWarning: DataFrame.applymap has been deprecated. Use Data
Frame.map instead.
  formatted_corr_matrix = correlation_matrix.applymap(lambda x: round(x, 2))
```


Correlation Matrix
Time V1 V2 V3 V4 V5 V6 V7 V8 V9 V10 V11 V12 V13 V14 V15 V16 V17 V18 V19 V20 V21 V22 V23 V24 V25 V26 V27 V28 Amount Class
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

Feature Architecture

Comprehensive Feature Set: 30 attributes

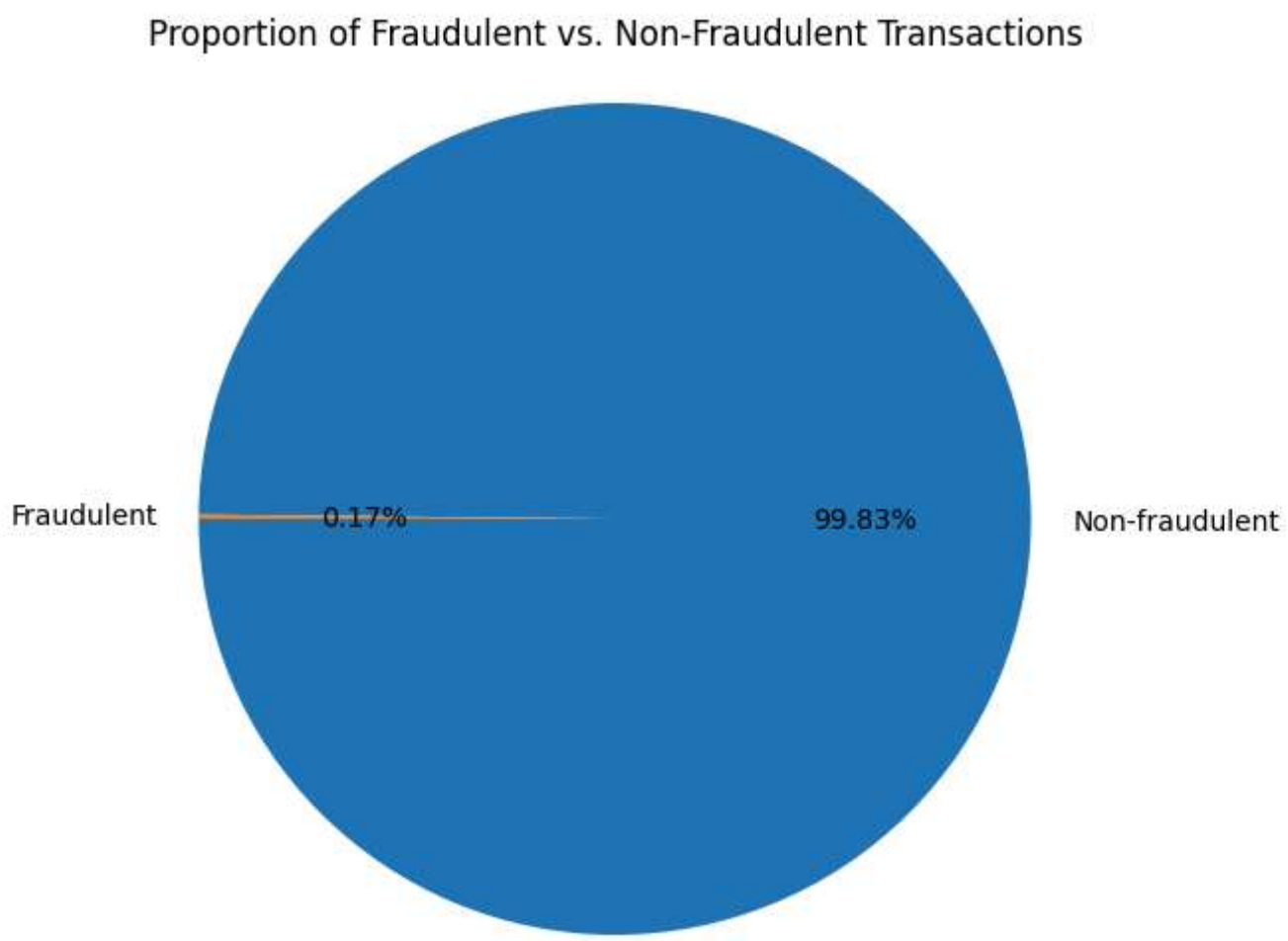
- 2 Explicitly Named Features:
  - Time of Transaction
  - Transaction Amount
- 28 Anonymized PCA-Transformed Features (V1-V28)
- No missing values

Data Complexity Challenges

- Extreme Class Imbalance
- High-Dimensional Feature Space
- Anonymized Predictive Variables
- Short-Duration Transaction Window

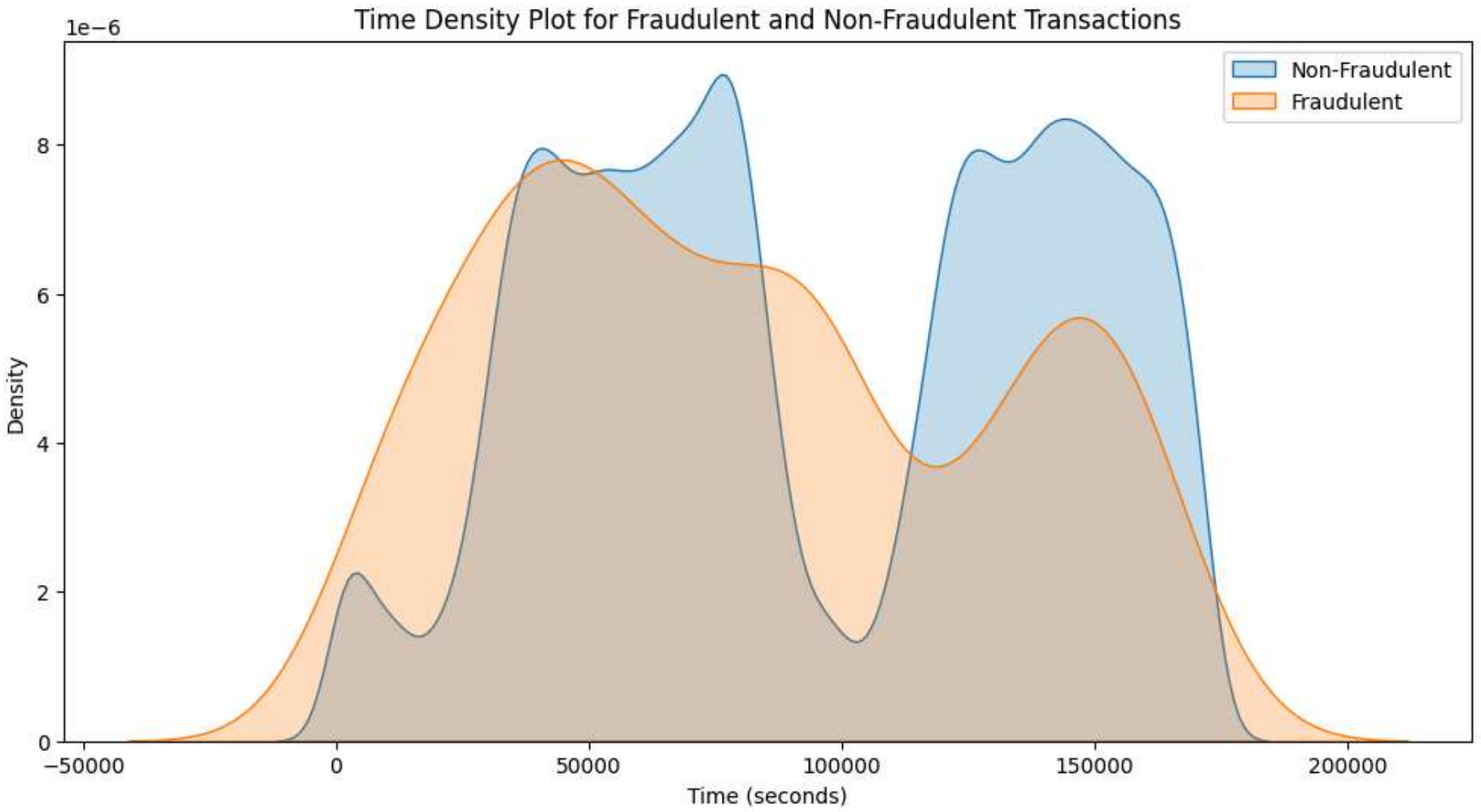
In an Anomaly Detection context, leaving the data imbalanced can actually be beneficial. Anomaly detection is typically designed to identify and learn from the normal (majority) class while detecting deviations (anomalies) that are rare occurrences. Low Correlation with the Target Variable: The 'Class' variable, representing fraudulent transactions, does not show high correlation with any single feature. This highlights the complexity of fraud detection, where no single feature is a strong indicator of fraud, necessitating a comprehensive analysis of multiple features.

In [17]:
```
# Plot a pie chat for showing imbalance
pu.pie_chart(ccds)
```



In [5]:
```
# Separate fraudulent and non-fraudulent transactions
fraud_transactions = ccds[ccds['Class'] == 1]
non_fraud_transactions = ccds[ccds['Class'] == 0]
# Plot the density of transactions over time
plt.figure(figsize=(12, 6))
sns.kdeplot(non_fraud_transactions['Time'], label='Non-Fraudulent', color='#1f77b4', fill=True)
sns.kdeplot(fraud_transactions['Time'], label='Fraudulent', color='#ff7f0e', fill=True)
plt.title('Time Density Plot for Fraudulent and Non-Fraudulent Transactions')
plt.xlabel('Time (seconds)')
plt.ylabel('Density')
```

```
plt.legend()
plt.show()
```



T-SNE

T-SNE(t-Distributed Stochastic Neighbor Embedding) is a dimensionality reduction technique used to visualize high-dimensional data in 2D or 3D space. Key characteristics for Anomaly Detection:

- Preserves local data structures
- Reveals clusters and separations in complex datasets
- Helps visualize data distributions

It helps Anomaly Detection Applications:

- Identify outliers visually
- Detect unusual data point clusters
- Preliminary data exploration before applying specific anomaly detection algorithms

The visualization reveals a significant challenge in anomaly detection: the substantial overlap between fraudulent and non-fraudulent transactions. This spatial proximity in the feature space suggests that distinguishing between legitimate and malicious transactions will require sophisticated, nuanced machine learning techniques capable of identifying extremely subtle discriminative patterns.

The high-dimensional proximity indicates that:

- Traditional binary classification approaches may struggle
- Advanced feature engineering is crucial
- Deep learning models with complex decision boundaries will be essential
- Unsupervised and semi-supervised techniques might offer more robust solutions

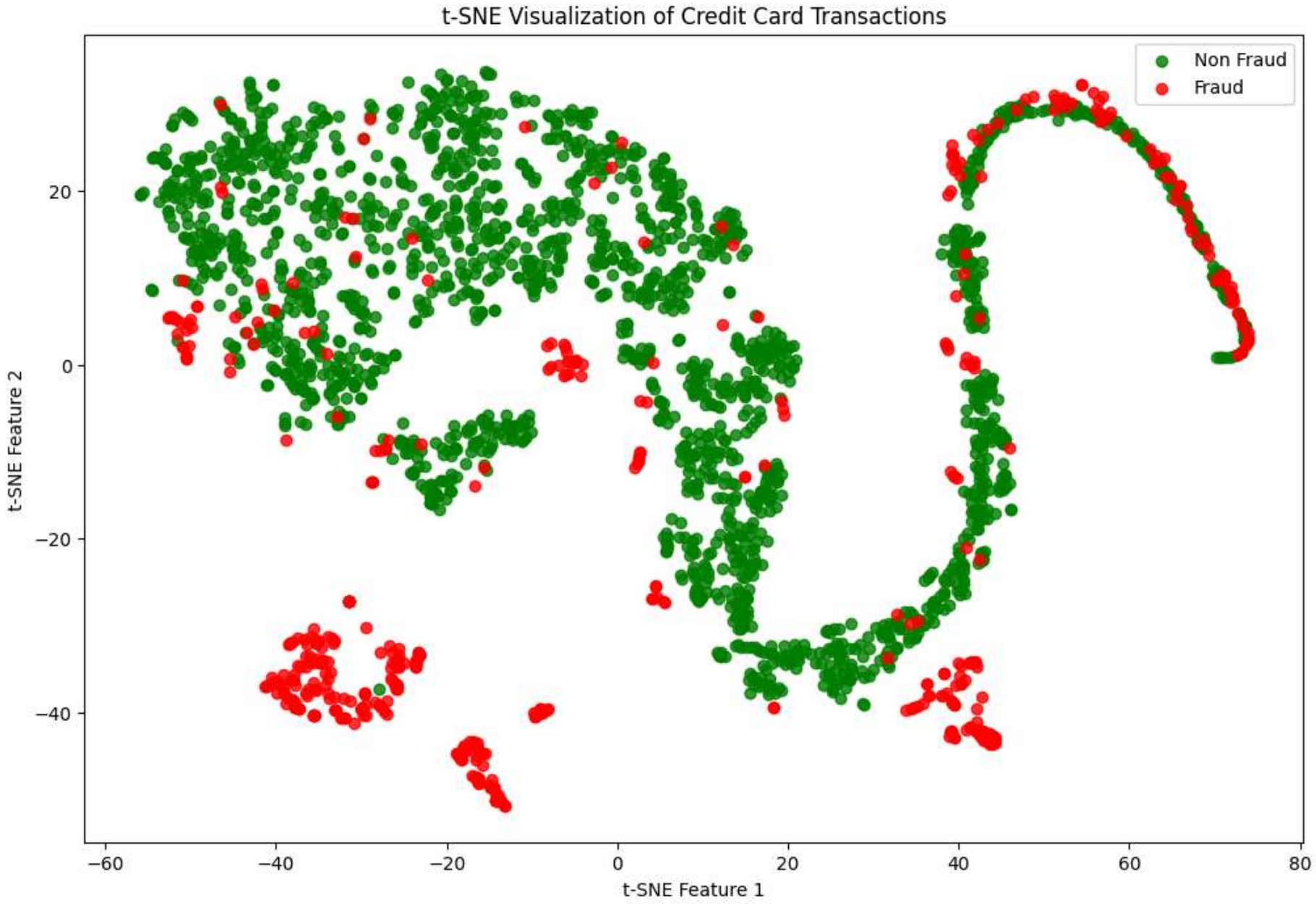
The visualization underscores the intricate nature of financial fraud detection, where malicious activities are strategically designed to mimic normal transactional behavior.

Methodological Approach Data Normalization Techniques

- Standardization of 'Amount' and 'Time' features
- Scaling to mitigate variable magnitude discrepancies

In [6]:
```
# T-SNE (t-Distributed Stochastic Neighbor Embedding)
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.manifold import TSNE
data = ccds.copy()
data["Time"] = data["Time"].apply(lambda x: x / 3600 % 24)
```

```
# Sample balanced dataset
non_fraud = data[data['Class'] == 0].sample(2000)
fraud = data[data['Class'] == 1]
df = pd.concat([non_fraud, fraud]).sample(frac=1).reset_index(drop=True)
X = df.drop(['Class'], axis=1).values
Y = df["Class"].values
# Apply t-SNE
tsne = TSNE(n_components=2, random_state=0)
X_t = tsne.fit_transform(X)
# Create scatter plot
plt.figure(figsize=(12, 8))
plt.scatter(X_t[Y == 0, 0], X_t[Y == 0, 1], marker='o', color='g', linewidth=1, alpha=0.8, label='Non Fraud')
plt.scatter(X_t[Y == 1, 0], X_t[Y == 1, 1], marker='o', color='r', linewidth=1, alpha=0.8, label='Fraud')
plt.title('t-SNE Visualization of Credit Card Transactions')
plt.xlabel('t-SNE Feature 1')
plt.ylabel('t-SNE Feature 2')
plt.legend(loc='best')
plt.show()
```



Deep Learning Model Architectures

The Difference Between Classification and Anomaly Detection

- **Classification**: – These models learn from both fraudulent and non-fraudulent transactions. – The goal is to classify each transaction based on learned patterns from labeled data. – They excel in distinguishing between known patterns of both categories but require labeled datasets for training. • **Anomaly Detection**: – These models focus on learning patterns from non-fraudulent transactions (normal behavior). – They then detect anomalies (frauds) based on deviations from these learned patterns. – This process is unsupervised and ideal for identifying outliers or rare events without needing explicit labels during training.

Deep Learning models to Anomaly Detection

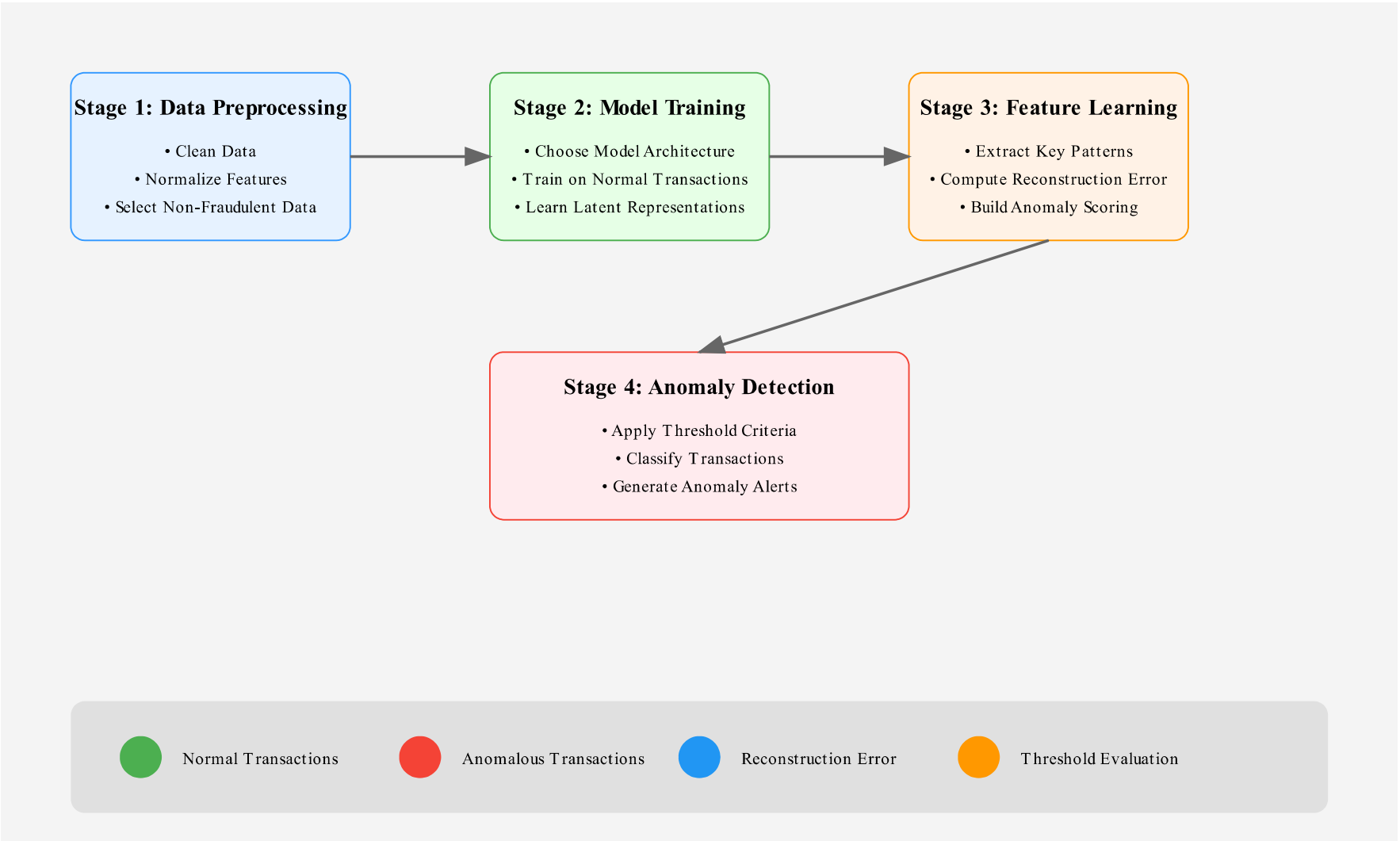
To effectively use Deep Learning models for anomaly detection, we need to focus on learning normal transactional behavior and then identify deviations.

- **Train on Non-Fraudulent Data**:
  - Train the models only on non-fraudulent transactions to learn normal patterns, similar to autoencoders.
- **Predict Anomalies**:
  - Implement an anomaly score based on reconstruction errors or prediction errors.
  - Set a threshold to differentiate between normal and anomalous transactions.

At the end of the predictions, for each model, we will calculate the classification_report, which provides a detailed performance summary of the anomaly detection model.

- **Anomalies vs. Normal Data**: In Anomaly Detection, the model classifies data points as either "normal" or "anomalous". When a model's reconstruction error exceeds a certain threshold, that data point is flagged as an anomaly.
- **Performance Metrics**: The classification_report from sklearn.metrics gives you key statistics like precision, recall, F1-score, and support for both the "normal" and "anomalous" classes. This way, we can assess how well the models distinguish between normal and anomalous data.

In summary, the classification_report helps understanding the effectiveness of anomaly detection's models by comparing the predicted labels (y_pred) with the true labels (y_test).



Long Short-Term Memory (LSTM)

- **Specialization**: Sequential temporal dependency analysis
- **Key Strengths**:– Memory retention of extended historical patterns– Sophisticated gradient flow management– Exceptional handling of time-series financial data

Layer Breakdown

- **Input Layer** (LSTM with 64 units):
  - **Purpose**: This layer is responsible for reading the input sequences and capturing both short-term and long-term dependencies within the data.
  - **64 Units**: This number of units is chosen to provide sufficient capacity for the model to learn complex patterns.
  - **return_sequences=True**: This ensures that the output of each time step is passed to the next layer, preserving the entire sequence of activities.
- **Dropout Layer** (0.2):
  - **Purpose**: Dropout helps prevent overfitting by randomly setting 20% of the input units to 0 at each update during training time. This encourages the model to generalize better by not relying too heavily on specific neurons.
- **Second LSTM Layer** (32 units):
  - **Purpose**: This second LSTM layer further processes the output from the first LSTM layer to capture more refined patterns.
  - **32 Units**: A smaller number of units is used in this layer to condense the information further, focusing on deeper sequential patterns.
  - **return_sequences=False**: Since this is the final LSTM layer, we set it to return only the last output in the sequence, which is then passed to the dense output layer.
- **Second Dropout Layer** (0.2):
  - **Purpose**: This dropout layer continues to prevent overfitting by dropping 20% of the units, ensuring the model remains robust and does not overfit on the training data.
- **Output Layer** (Dense with Sigmoid Activation):
  - **Purpose**: The dense layer with a single unit outputs the probability of a transaction being fraudulent.
  - **Sigmoid Activation**: The sigmoid activation function maps the output to a value between 0 and 1, making it suitable for binary classification tasks.

Summary

- **Stacked LSTM Layers**: The combination of stacked LSTM layers helps the model effectively capture short-term and long-term dependencies within the transactional data.
- **Dropout Layers**: These are crucial in preventing overfitting by randomly dropping units during training, promoting better generalization.
- **Output Layer**: The dense layer with sigmoid activation provides the final probability prediction for fraud detection.

In [7]:

```
#STEP 1: Import Libraries
import pandas as pd
import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Input, LSTM, SimpleRNN, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.optimizers import Adam
import matplotlib.pyplot as plt

#STEP2: Preprocess the Data
# Separate features and labels
X = ccds.drop('Class', axis=1)
y = ccds['Class']

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Separate non-fraudulent transactions for training
X_train = X_scaled[y == 0]

# Use both non-fraudulent and fraudulent transactions for testing
X_test = X_scaled
y_test = y

# Reshape input if necessary
X_train_reshaped = X_train.reshape(X_train.shape[0], 1, X_train.shape[1])
X_test_reshaped = X_test.reshape(X_test.shape[0], 1, X_test.shape[1])


#STEP 3: Define the LSTM Model
# Define the LSTM model
model_lstm = Sequential(name='LSTM_AnomalyDetectionModel')
model_lstm.add(Input(shape=(1, X_train_reshaped.shape[2]), name='Input_Layer'))
model_lstm.add(LSTM(64, return_sequences=True, name='LSTM_Layer_1'))
model_lstm.add(Dropout(0.2, name='Dropout_Layer_1'))
model_lstm.add(LSTM(32, return_sequences=False, name='LSTM_Layer_2'))
```

```
model_lstm.add(Dropout(0.2, name='Dropout_Layer_2'))
model_lstm.add(Dense(X_train_reshaped.shape[2], activation='sigmoid', name='Output_Layer'))

model_lstm.compile(loss='mean_squared_error', optimizer=Adam(learning_rate=0.001))

#STEP 4: Train the Model
# Train the LSTM model
early_stopping = EarlyStopping(monitor='val_loss', patience=3, restore_best_weights=True)
history_lstm = model_lstm.fit(X_train_reshaped, X_train_reshaped, epochs=20, batch_size=64, validation_data=(X_test_reshaped, X_t
print(model_lstm.summary())

#STEP 5: Evaluate the Model
# Calculate reconstruction error for LSTM
# Evaluate in batches
batch_size = 1000
mse_lstm = []
for start in range(0, X_test_reshaped.shape[0], batch_size):
    end = min(start + batch_size, X_test_reshaped.shape[0])
    reconstructed_lstm_batch = model_lstm.predict(X_test_reshaped[start:end])
    mse_lstm_batch = np.mean(np.power(X_test_reshaped[start:end]-reconstructed_lstm_batch, 2), axis=2).flatten() # Ensure mse_lst
    mse_lstm.extend(mse_lstm_batch) # Append each batch's MSE

mse_lstm = np.array(mse_lstm) # Convert to numpy array
```

```
Epoch 1/20
4443/4443 ━━━━━━━━━━━━━━━━━━━━ 29s 5ms/step - loss: 0.9741 - val_loss: 1.0000
Epoch 2/20
4443/4443 ━━━━━━━━━━━━━━━━━━━━ 24s 5ms/step - loss: 0.9564 - val_loss: 1.0000
Epoch 3/20
4443/4443 ━━━━━━━━━━━━━━━━━━━━ 26s 6ms/step - loss: 0.9577 - val_loss: 1.0000
Epoch 4/20
4443/4443 ━━━━━━━━━━━━━━━━━━━━ 24s 5ms/step - loss: 0.9707 - val_loss: 0.9998
Epoch 5/20
4443/4443 ━━━━━━━━━━━━━━━━━━━━ 25s 6ms/step - loss: 0.9724 - val_loss: 0.9998
Epoch 6/20
4443/4443 ━━━━━━━━━━━━━━━━━━━━ 23s 5ms/step - loss: 0.9642 - val_loss: 0.9998
Epoch 7/20
4443/4443 ━━━━━━━━━━━━━━━━━━━━ 24s 5ms/step - loss: 0.9661 - val_loss: 0.9998
Epoch 8/20
4443/4443 ━━━━━━━━━━━━━━━━━━━━ 22s 5ms/step - loss: 0.9622 - val_loss: 0.9996
Epoch 9/20
4443/4443 ━━━━━━━━━━━━━━━━━━━━ 24s 5ms/step - loss: 0.9599 - val_loss: 0.9996
Epoch 10/20
4443/4443 ━━━━━━━━━━━━━━━━━━━━ 26s 6ms/step - loss: 0.9541 - val_loss: 0.9996
Epoch 11/20
4443/4443 ━━━━━━━━━━━━━━━━━━━━ 26s 6ms/step - loss: 0.9835 - val_loss: 0.9996
```

Model: "LSTM_AnomalyDetectionModel"

Layer (type)	Output Shape	Param #
LSTM_Layer_1 (LSTM)	(None, 1, 64)	24,320
Dropout_Layer_1 (Dropout)	(None, 1, 64)	0
LSTM_Layer_2 (LSTM)	(None, 32)	12,416
Dropout_Layer_2 (Dropout)	(None, 32)	0
Output_Layer (Dense)	(None, 30)	990

Total params: 113,180 (442.11 KB)

Trainable params: 37,726 (147.37 KB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 75,454 (294.75 KB)