Credit Card Fraud Prediction

Problem Statement

- Credit cards offer convenience for purchases but carry the risk of fraud.
- Fraudulent transactions result in unauthorized charges for customers.
- This project aims to build a classification model to accurately detect fraudulent credit card transactions.

Dataset

- The dataset contains European credit card transactions from September 2013.
- **Key Points:**
  - Two days of transactions
  - 492 frauds out of 284,807 transactions
  - Highly imbalanced dataset (0.172% frauds)

In [ ]:

```
```

Importing all required python library

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns

from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifie
from xgboost import XGBClassifier

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import confusion_matrix, classification_report, f1_score,
from sklearn.preprocessing import OneHotEncoder, LabelEncoder, OrdinalEncoder,

from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
import pickle
import json

import matplotlib.pyplot as plt
%matplotlib inline
```

In [1]:

```

```

Let's load creditcard.csv

In [2]:

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

In [2]:

```

```

let's see how our dataframe look like

In [3]:

```
df.head()
```

Out[3]:

	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

In [3]:

```

```

Let's performe some descriptive statistics on main dataframe df

shape and data tyeps of each columns info

In [4]:

```
df.shape
```

Out[4]:

```
(284807, 31)
```

In [5]:
```
df.info()
```

```
<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
```

In [5]:
```

```

Data Preprocessing

check for duplicated data points (rows in df DataFrame)

In [6]:
```
df.duplicated().sum()
```

Out[6]:
```
1081
```

In [7]:
```
# let's drop dublicated data-points
df.drop_duplicates(keep = 'first', inplace = True)
```

In [8]:
```
df.duplicated().sum()
```

Out[8]: 0

fine now there is no duplicated data points

In [8]:
```
```

Shuffle Data:

In [9]:
```
# Let's shuffle the whole dataframe and reset the index.
df = df.sample(frac=1, random_state=42).reset_index(drop = True)
```

In [9]:
```
```

Check for missing values

Let's check that is any null values into my dataframe df or not

In [10]:
```
df.isnull().sum()
```

Out[10]:
```
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
```

No! There is no missing values in my DataFrame df, so it's again fine

In [10]:
```

```

Let's show high level top stats from DataFrame df

In [11]:
```
df.describe().T
```

Out[11]:

	count	mean	std	min	25%	50%	
Time	283726.0	94811.077600	47481.047891	0.000000	54204.750000	84692.500000	139298.
V1	283726.0	0.005917	1.948026	-56.407510	-0.915951	0.020384	1.
V2	283726.0	-0.004135	1.646703	-72.715728	-0.600321	0.063949	0.
V3	283726.0	0.001613	1.508682	-48.325589	-0.889682	0.179963	1.
V4	283726.0	-0.002966	1.414184	-5.683171	-0.850134	-0.022248	0.
V5	283726.0	0.001828	1.377008	-113.743307	-0.689830	-0.053468	0.
V6	283726.0	-0.001139	1.331931	-26.160506	-0.769031	-0.275168	0.
V7	283726.0	0.001801	1.227664	-43.557242	-0.552509	0.040859	0.
V8	283726.0	-0.000854	1.179054	-73.216718	-0.208828	0.021898	0.
V9	283726.0	-0.001596	1.095492	-13.434066	-0.644221	-0.052596	0.
V10	283726.0	-0.001441	1.076407	-24.588262	-0.535578	-0.093237	0.
V11	283726.0	0.000202	1.018720	-4.797473	-0.761649	-0.032306	0.
V12	283726.0	-0.000715	0.994674	-18.683715	-0.406198	0.139072	0.
V13	283726.0	0.000603	0.995430	-5.791881	-0.647862	-0.012927	0.
V14	283726.0	0.000252	0.952215	-19.214325	-0.425732	0.050209	0.
V15	283726.0	0.001043	0.914894	-4.498945	-0.581452	0.049299	0.
V16	283726.0	0.001162	0.873696	-14.129855	-0.466860	0.067119	0.
V17	283726.0	0.000170	0.842507	-25.162799	-0.483928	-0.065867	0.
V18	283726.0	0.001515	0.837378	-9.498746	-0.498014	-0.002142	0.
V19	283726.0	-0.000264	0.813379	-7.213527	-0.456289	0.003367	0.
V20	283726.0	0.000187	0.769984	-54.497720	-0.211469	-0.062353	0.
V21	283726.0	-0.000371	0.723909	-34.830382	-0.228305	-0.029441	0.
V22	283726.0	-0.000015	0.724550	-10.933144	-0.542700	0.006675	0.
V23	283726.0	0.000198	0.623702	-44.807735	-0.161703	-0.011159	0.
V24	283726.0	0.000214	0.605627	-2.836627	-0.354453	0.041016	0.
V25	283726.0	-0.000232	0.521220	-10.295397	-0.317485	0.016278	0.
V26	283726.0	0.000149	0.482053	-2.604551	-0.326763	-0.052172	0.
V27	283726.0	0.001763	0.395744	-22.565679	-0.070641	0.001479	0.
V28	283726.0	0.000547	0.328027	-15.430084	-0.052818	0.011288	0.
Amount	283726.0	88.472687	250.399437	0.000000	5.600000	22.000000	77.
Class	283726.0	0.001667	0.040796	0.000000	0.000000	0.000000	0.

In [11]:

```
```

Check distribution of classes (Understanding Class Imbalance)

Because this is a Credit Card Fraud Detection System,

the data may be highly imbalanced.

So let's check.

This is a binary classification problem and my target clumn is 'Class', let's check imblance on feature 'Class'

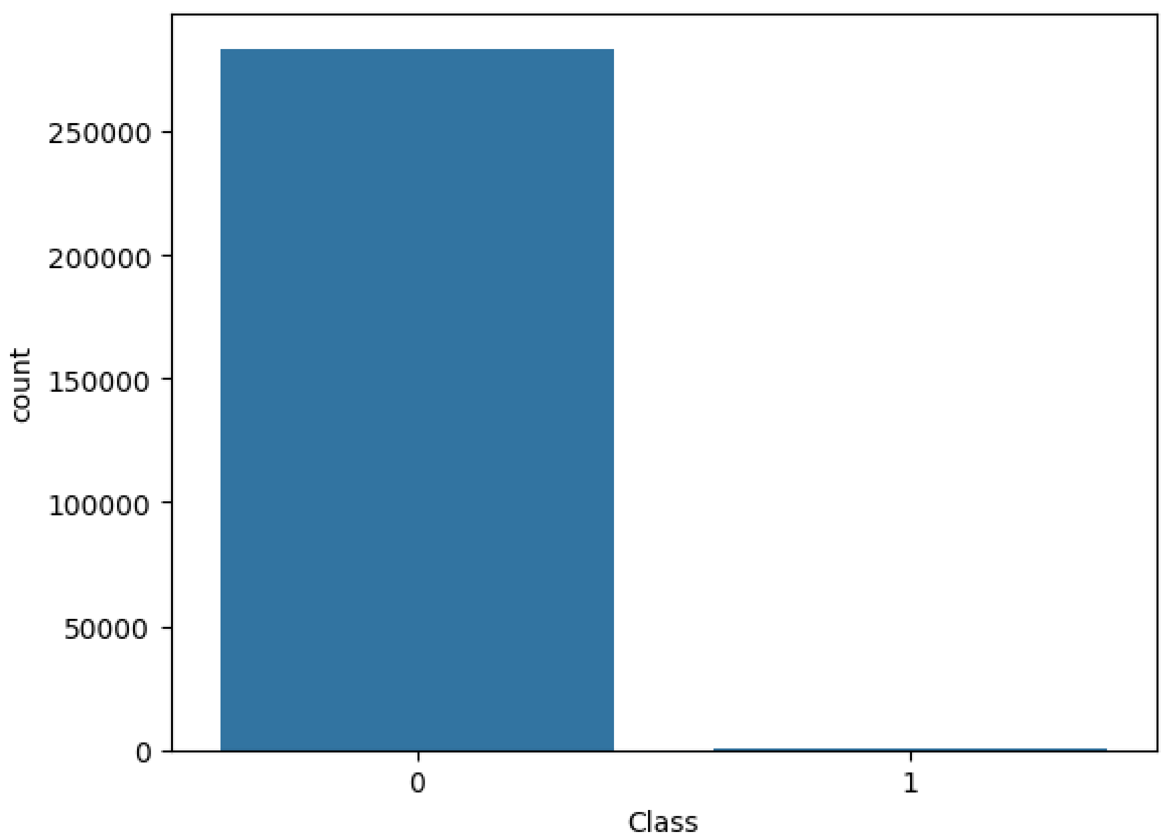
In [12]:

```
print(f"No Frauds: {round(100*(df['Class'].value_counts()[0]/df.shape[0]), 2)}
print(f"Frauds: {round(100*(df['Class'].value_counts()[1]/df.shape[0]), 2)} %
```

```
No Frauds: 99.83 % of the dataset
Frauds: 0.17 % of the dataset
```

In [13]:

```
# Visualization
sns.countplot(x='Class', data=df)
plt.show()
```



In [14]:
```
df['Class'].value_counts()
```

Out[14]:
```
0    283253
1       473
Name: Class, dtype: int64
```

In [14]:

Balancing the data. Addressing Imbalance (Undersampling):

- Here we can see easily say that data is highly imblance
- If we leave as it is then there will big challenges to train my model and also this is biases towards 0
- To stop do that simply we need to convert this imblance data into blance data
- Here minority class 1 has 473 data points that is enough for train ML model
- So here we do under sampling

In [15]:
```
df_fraud = df[df['Class'] == 1]
df_nonFraud = df[df['Class'] == 0].sample(473, random_state = 42)
df = pd.concat([df_fraud, df_nonFraud], axis=0).sample(frac = 1, random_state
```

In [16]:
```
df['Class'].value_counts()
```

Out[16]:
```
1    473
0    473
Name: Class, dtype: int64
```

Now here we can see train data is blanced right now. Fine

In [16]:

In [16]:

Exploratory Data Analysis (EDA), Feature Engineering, and Selection

In [17]:
```
sns.set_style(style='darkgrid')
```

let's see which columns is highily coreelated with 'Class' target column

- You can see that a very high correlation means good features (columns) that we stored in the relevant_columns variable, and we skip all other features (columns) that have a correlation less than 0.2 and greater than -0.2.

In [18]:
```
relevant_columns = df.corr()[(df.corr()['Class'] >= 0.2) | (df.corr()['Class']
df.corr()[(df.corr()['Class'] >= 0.2) | (df.corr()['Class'] <= -0.2)][['Class'
```

Out[18]:

	V1	V2	V3	V4	V5	V6	V7	V9	V10
Class	-0.41548	0.480987	-0.562283	0.70504	-0.353406	-0.410617	-0.46762	-0.564377	-0.627

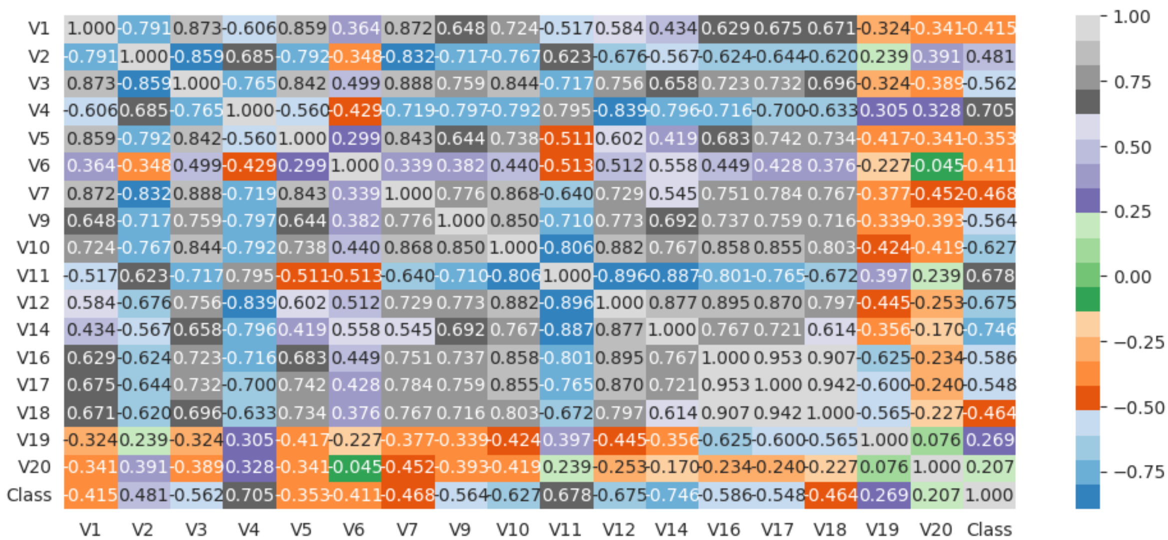
In [18]:

In [19]:
```
# Let's modify dataframe the original columns to these selected columns chosen
df = df.loc[:, relevant_columns]
```

In [19]:

Now let's see heatmap of all features with out target 'Class' column

In [20]:
```
plt.figure(figsize = (12, 5))
sns.heatmap(df.corr(), annot = True, fmt = ".3f", cmap="tab20c");
```



In [20]:

In [20]:

Outlier Treatment (IQR):

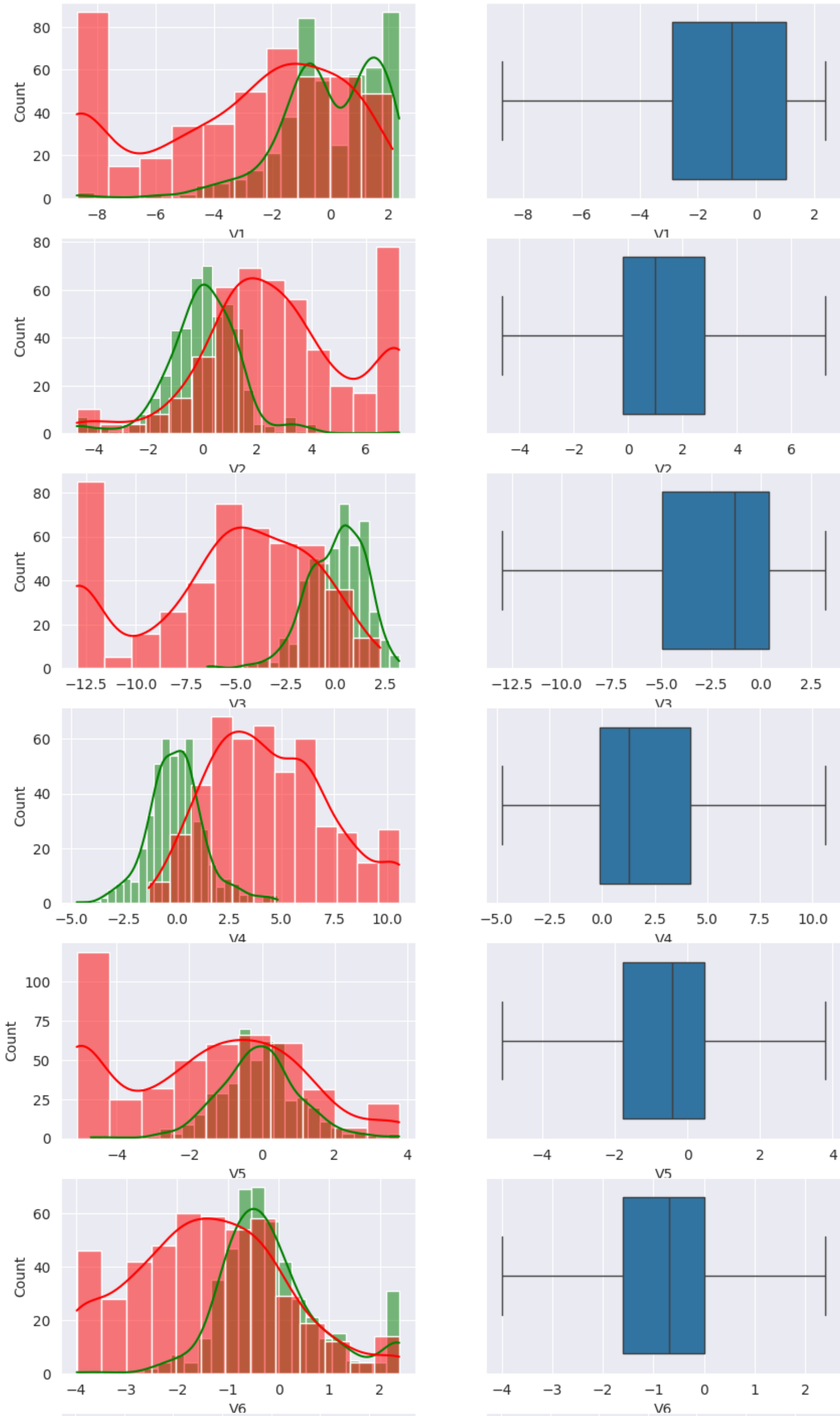
In [21]:
```
def apply_IQR(series_col):
    """
    This function takes a numeric series and returns a new series with outlier

    Args:
    series_col: The numeric series to be cleaned.

    Returns:
    A new series with outliers replaced by IQR bounds.

    """

    Q1 = series_col.quantile(0.25)
    Q3 = series_col.quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    # cleaned_series = series_col.clip(lower_bound, upper_bound)
    return lower_bound, upper_bound

IQR_dic = {}
for col in df.columns:
    lower_bound, upper_bound = apply_IQR(df[col])
    df[col] = df[col].clip(lower_bound, upper_bound)
    IQR_dic[col] = {"lower_bound": lower_bound, "upper_bound": upper_bound}
```

In [21]:

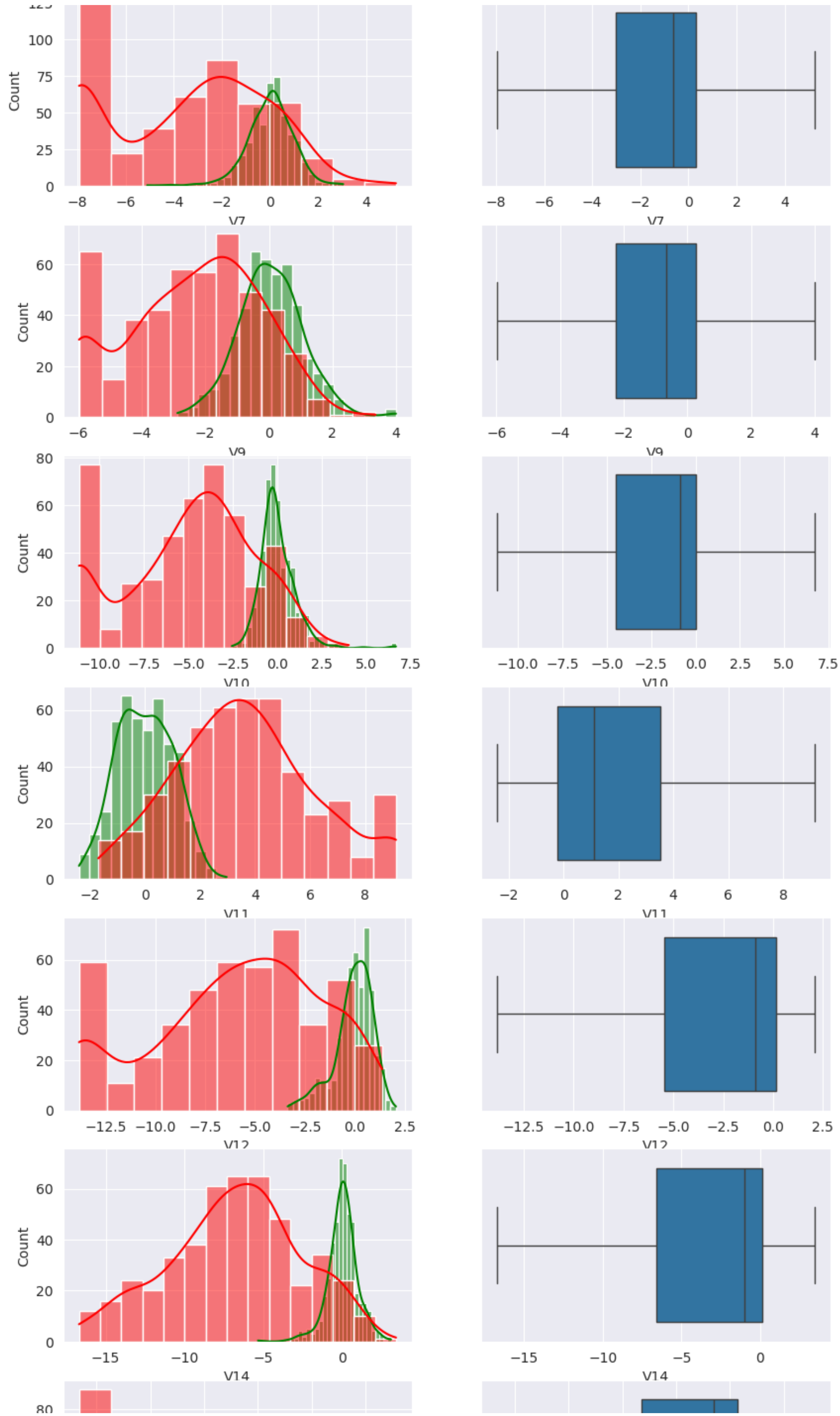
Visualizations:

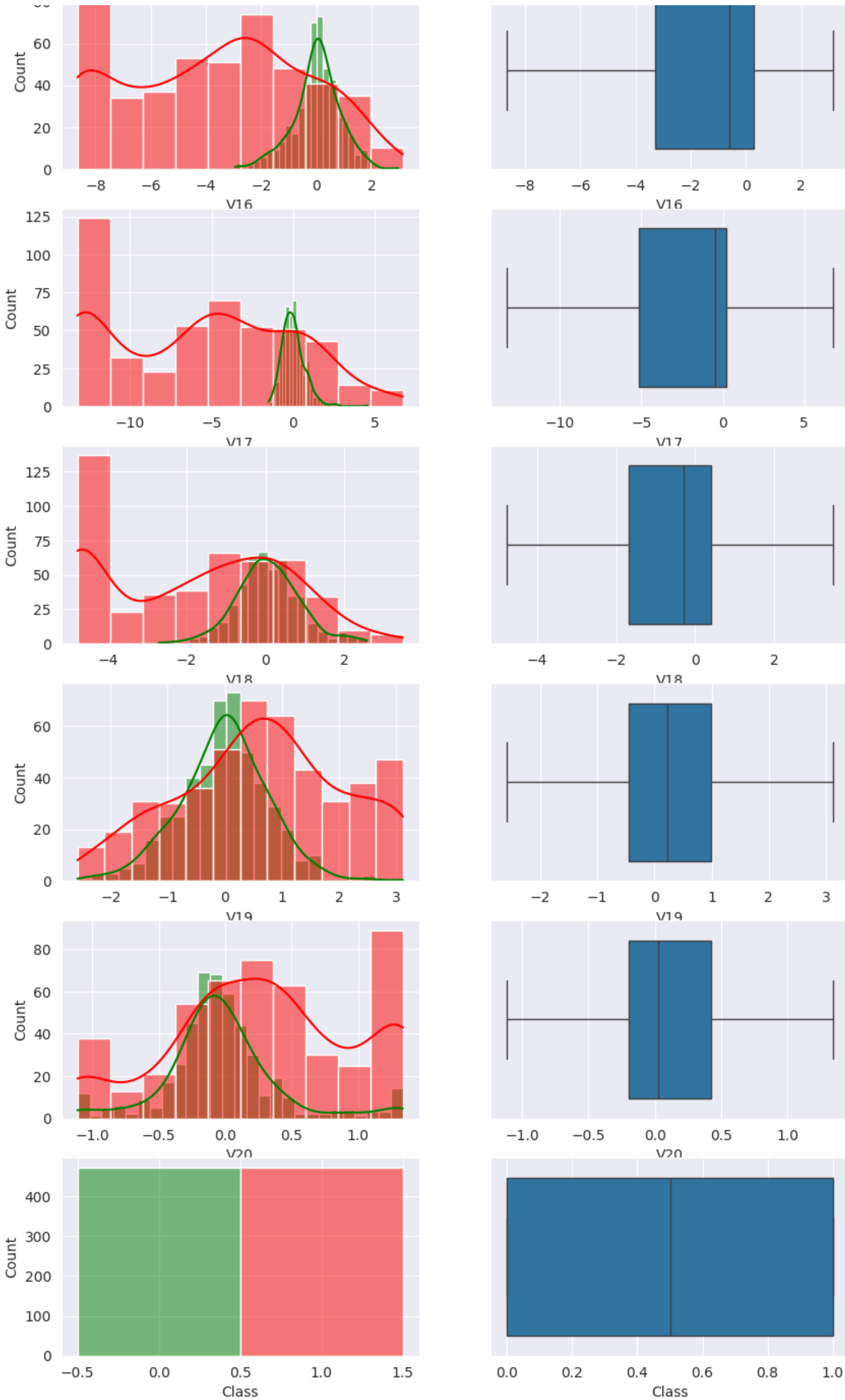
In [22]:
```
# plt.figure(figsize=(10, 7))
print("Green Indicate: Not Fraud, and Red indicate: Fraud")

fig, ax = plt.subplots(len(df.columns),2, figsize = (10,len(df.columns)*3))
for idx, cname in zip(range(0, len(df.columns)), list(df.columns)):

    sns.histplot(df[df["Class"] == 0][cname], color = 'g', kde=True, ax = ax[i
    sns.histplot(df[df["Class"] == 1][cname], color = 'r', kde=True, ax = ax[i

    sns.boxplot(x = df[cname], ax = ax[idx][1]);
```

```
Green Indicate: Not Fraud, and Red indicate: Fraud
```



Count
V1
Count
V2
Count
V3
Count
V4
Count
V5
Count
V6


Count
V7
V7
Count
V9
V9
Count
V10
V10
Count
V11
V11
Count
V12
V12
Count
V14
V14


Count
V16
V16
Count
V17
V17
Count
V18
V18
Count
V19
V19
Count
V20
V20
Count
Class
Class

In [22]:

```python

```

Train/Test Split - Apply a sampling distribution to find the best split.

In [23]:

```python
X_train, X_test, y_train, y_test = train_test_split(df.drop('Class', axis = 1)
```

In [24]:

```python
X_train.shape, y_train.shape, X_test.shape, y_test.shape
```

Out[24]:

```
((756, 17), (756,), (190, 17), (190,))
```

In [24]:

```python

```

Hyperparameter Tuning/Model Improvement

In [25]:
```
model_params = {

    'lr': {
        'model': LogisticRegression(),
        'params_grid': {
            'penalty': ['l1', 'l2'],
            'C': [0.01, 0.1, 1.0, 10.0], # Test wide range for C
        }
    },

    'knn': {
        'model': KNeighborsClassifier(), # Classifier version
        'params_grid': {
            'n_neighbors': [3, 5, 7, 9, 11, 15],
            'weights': ['uniform', 'distance'],
        }
    },

    'svm': {
        'model': SVC(),
        'params_grid': {
            'kernel': ['linear', 'poly', 'rbf', 'sigmoid'],
            'C': [1, 5, 10, 20],
            'degree': [2, 3, 5]
        }
    },

    'rf': {
        'model': RandomForestClassifier(), # Use the classifier version
        'params_grid': {
            'n_estimators': [50, 100, 200],
            'max_depth': [None, 3, 5, 8],
            'max_samples' : [ 0.5, 0.75, 1]
        }
    },


    'gbc': {
        'model': GradientBoostingClassifier(), # Classifier version
        'params_grid': {
            'n_estimators': [50, 100, 200],
            'max_depth': [2, 3, 5],
            'learning_rate': [0.01, 0.05, 0.1],
        }
    },

    'xgbc': {
        'model': XGBClassifier(),  # Classifier version
        'params_grid': {
            'gamma': [0, 0.1, 0.2, 0.5],
            'max_depth': [3, 4, 5],
            'learning_rate': [0.05, 0.1, 0.2],
            'reg_lambda': [0.5, 1.0, 5.0],
        }
    },

}
```

In [25]:

In [ ]:
```
score = {
    "model": [],
    "best_score_": [],
    "best_params_": [],
}

for itm in model_params :
    print(model_params[itm]['model'])
    clf = GridSearchCV(model_params[itm]['model'], param_grid=model_params[itm
    clf.fit(df.drop('Class', axis = 1).values, df['Class'].values)

    score["model"].append(itm)
    score["best_score_"].append(clf.best_score_)
    score["best_params_"].append(clf.best_params_)
```

In [27]:
```
score_df = pd.DataFrame(score)
score_df
```

Out[27]:

	model	best_score_	best_params_
0	lr	0.932314	{'C': 10.0, 'penalty': 'l2'}
1	knn	0.932325	{'n_neighbors': 7, 'weights': 'distance'}
2	svm	0.933383	{'C': 5, 'degree': 2, 'kernel': 'linear'}
3	rf	0.935494	{'max_depth': None, 'max_samples': 0.75, 'n_es...
4	gbc	0.934425	{'learning_rate': 0.05, 'max_depth': 3, 'n_est...
5	xgbc	0.934431	{'gamma': 0, 'learning_rate': 0.05, 'max_depth...

In [27]:

Model Training

In [28]:
```
model_name, model_best_score_, model_best_params_ = score_df.sort_values(by =

print(f"Best Model: {model_name} | Score: {model_best_score_} | Params: {model
```

```
Best Model: rf | Score: 0.9354942912837648 | Params: {'max_depth': None, 'max
_samples': 0.75, 'n_estimators': 50}
```

In [28]:

In [29]:
```
best_model = model_params[model_name]['model']
best_model.set_params(**model_best_params_)
print(f"We initialize the {best_model}\n\nmodel with appropriate parameters: {
```

```
We initialize the RandomForestClassifier(max_samples=0.75, n_estimators=50)

model with appropriate parameters: {'max_depth': None, 'max_samples': 0.75,
'n_estimators': 50}
```

In [30]:
```
best_model.fit(X_train, y_train)
```

Out[30]:
```
RandomForestClassifier(max_samples=0.75, n_estimators=50)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [30]:

Model Validation and the accuracy of the model:

In [31]:
```
y_pred_train = best_model.predict(X_train)
y_pred_test = best_model.predict(X_test)
```

In [32]:
```
print(f"Confusion matrix for train dataset:\n{confusion_matrix(y_train, y_pred
print(f"Classification Report for train dataset:\n\n{classification_report(y_t
```

```
Confusion matrix for train dataset:
[[378   0]
 [  2 376]]


Classification Report for train dataset:

              precision    recall  f1-score   support

           0       0.99      1.00      1.00       378
           1       1.00      0.99      1.00       378

    accuracy                           1.00       756
   macro avg       1.00      1.00      1.00       756
weighted avg       1.00      1.00      1.00       756
```

In [32]:

In [33]:
```
print(f"Confusion matrix for test dataset:\n{confusion_matrix(y_test, y_pred_t
print(f"Classification Report for test dataset:\n\n{classification_report(y_te
```

```
Confusion matrix for test dataset:
[[94  1]
 [14 81]]


Classification Report for test dataset:

              precision    recall  f1-score   support

           0       0.87      0.99      0.93        95
           1       0.99      0.85      0.92        95

    accuracy                           0.92       190
   macro avg       0.93      0.92      0.92       190
weighted avg       0.93      0.92      0.92       190
```

In [33]:

Best Model all accuracy metrics

In [34]:
```
pd.DataFrame({
    "Accuracy": [accuracy_score(y_train, y_pred_train), accuracy_score(y_test,
    "Precision": [precision_score(y_train, y_pred_train), precision_score(y_te
    "Recall": [recall_score(y_train, y_pred_train), recall_score(y_test, y_pre
    "F1 Score": [f1_score(y_train, y_pred_train), f1_score(y_test, y_pred_test
    "Roc Auc Score": [roc_auc_score(y_train, y_pred_train), roc_auc_score(y_te
}, index=["Train", "Test"])
```

Out[34]:

	Accuracy	Precision	Recall	F1 Score	Roc Auc Score
Train	0.997354	1.000000	0.994709	0.997347	0.997354
Test	0.921053	0.987805	0.852632	0.915254	0.921053

In [34]:

Let's save all necessary files for model deployment

In [35]:
```
# Save thresholds as JSON
with open('iqr_thresholds.json', 'w') as f:
    json.dump(IQR_dic, f)
```

In [36]:
```
with open("clf.pkl", 'wb') as outfile :
    pickle.dump(best_model, outfile)
```

In [36]: