Credit_Card_Fraud_Detection

September 22, 2025

1 Credit Card Fraud Detection Project

Author: Akshay Bhujbal
Project Type: AI / Machine Learning Portfolio Project

1.1 Project Overview

This project demonstrates a **Credit Card Fraud Detection system** using a **Random Forest Classifier**.
The app allows users to:

1. Select a **sample transaction** from the dataset.

2. Enter **all 30 features manually**.

3. Lookup **any transaction by its Index**.

The model was trained on ~284,000 transactions with 30 features (`Time`, `V1–V28`, `Amount`) and predicts whether a transaction is **fraudulent or not**.

2 Load Dataset

- **pd.read_csv** loads the CSV file into a DataFrame.
- **data.head()** shows the first 5 rows to check how your data looks.

[1]:
```
import pandas as pd

# Load dataset
data = pd.read_csv(r"C:
↪\Users\Lenovo\OneDrive\Desktop\Projects_Sorted\AI-Portfolio\Showcase-Projects\Credit-Card-F
↪csv")

# See first few rows
data.head()
```

[1]:
```
   Time        V1        V2        V3        V4        V5        V6        V7  \
0   0.0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
1   0.0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
2   1.0 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
```

```
3   1.0 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
4   2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

         V8        V9  …       V21       V22       V23       V24       V25  \
0  0.098698  0.363787  … -0.018307  0.277838 -0.110474  0.066928  0.128539
1  0.085102 -0.255425  … -0.225775 -0.638672  0.101288 -0.339846  0.167170
2  0.247676 -1.514654  …  0.247998  0.771679  0.909412 -0.689281 -0.327642
3  0.377436 -1.387024  … -0.108300  0.005274 -0.190321 -1.175575  0.647376
4 -0.270533  0.817739  … -0.009431  0.798278 -0.137458  0.141267 -0.206010

        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]
```

3 Exploratory Data Analysis (EDA)

3.1 Check basic info:

- `data.shape` → shows rows and columns.
- `data.info()` → shows data types and missing values.
- `data.describe()` → shows mean, min, max, etc. for numeric features.

[2]:
```python
# Shape of dataset
print(data.shape)
```

```
(284807, 31)
```

[3]:
```python
# Column info
print(data.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
None
```

[4]:
```python
# Summary statistics
print(data.describe())
```

```
                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]
```

3.2 Check for missing values:

- `isnull().sum()` counts missing values per column.
- This dataset has **no missing values**, so we're good.

[5]:
```python
print(data.isnull().sum())
```

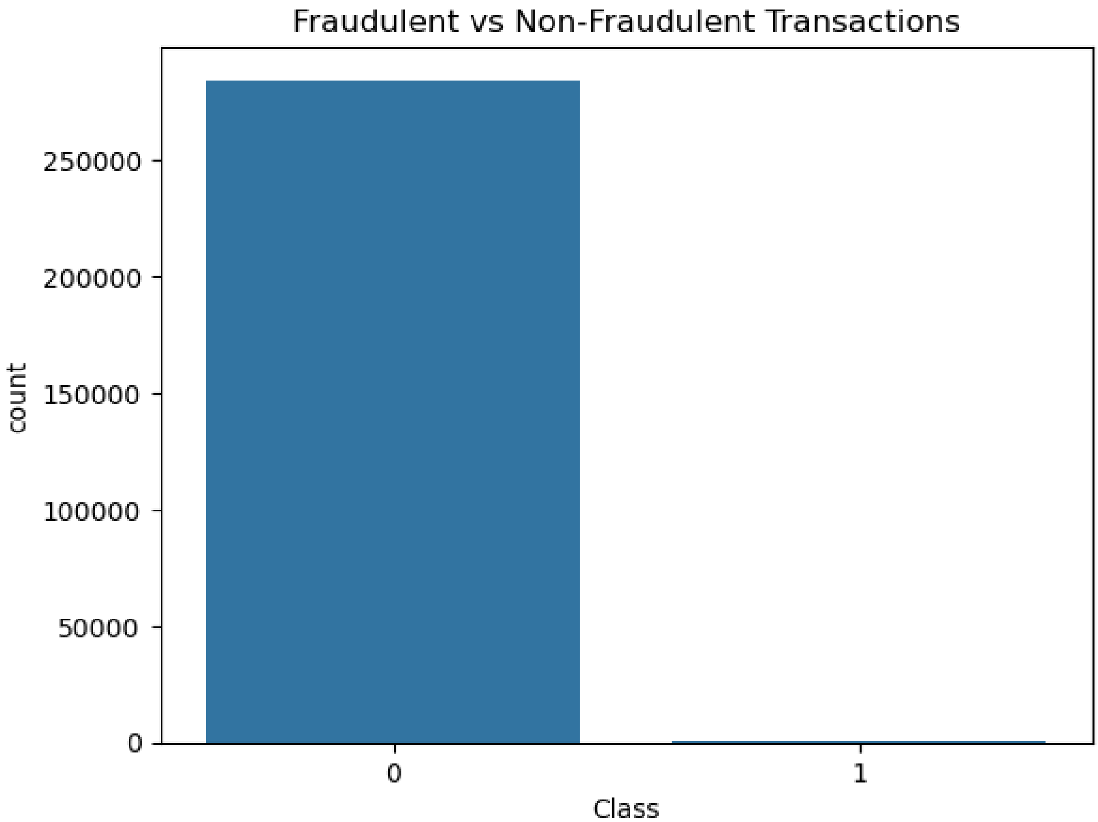
```
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
```

```
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
```

3.3 Visualize class distribution:

- Shows how many transactions are **fraudulent (1)** vs **non-fraudulent (0).**
- The dataset is **highly imbalanced** → very few frauds.

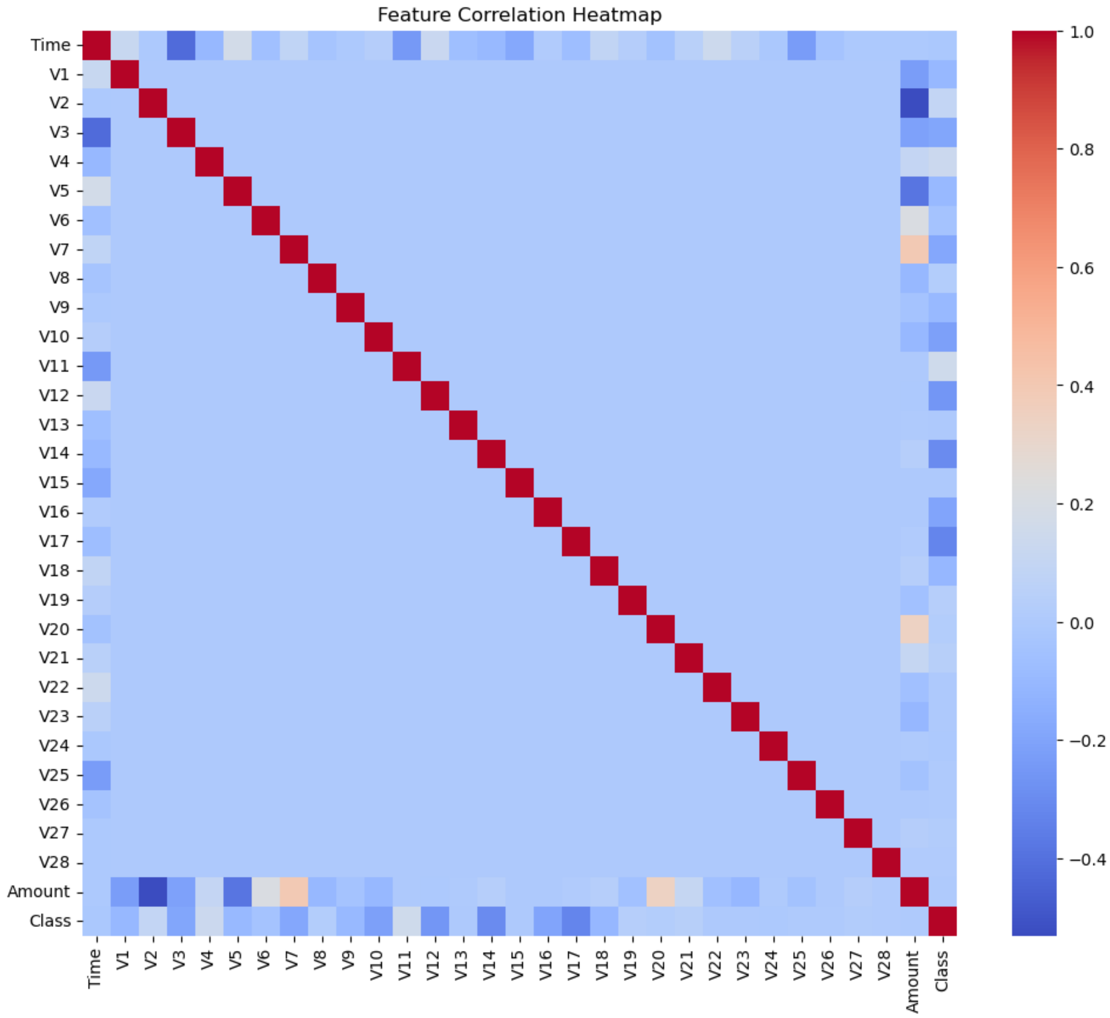
[6]:
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.countplot(x='Class', data=data)
plt.title('Fraudulent vs Non-Fraudulent Transactions')
plt.show()
```



3.4 Check correlations

- Helps see which features are strongly correlated with `Class` (fraud).
- Useful for feature selection later.

[7]:
```
plt.figure(figsize=(12,10))
sns.heatmap(data.corr(), cmap='coolwarm', annot=False)
plt.title('Feature Correlation Heatmap')
plt.show()
```



4 Prepare Data for Machine Learning

4.1 Split features and target

[8]:
```
X = data.drop('Class', axis=1)  # All columns except 'Class'
y = data['Class']               # Target
```

4.2 Split into train/test

- `stratify=y` ensures the same ratio of fraud/non-fraud in train & test sets.

[9]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
```

```
)
```

4.3 Scale features

- Scaling helps models like Logistic Regression perform better.
- Random Forest doesn't need it, but scaling is good practice.

[10]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

5 Train a Machine Learning Model

We'll use **Random Forest Classifier:**

- Random Forest → robust and handles imbalance better than simple models.
- classification_report → shows precision, recall, F1-score for each class.
- Accuracy is not enough → focus on **-precision/recall for fraud class**.

[11]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score

model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)
```

[11]:
```
RandomForestClassifier(random_state=42)
```

[13]:
```
y_pred = model.predict(X_test)
```

[14]:
```
# Evaluate
print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9995962220427653
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.94      0.82      0.87        98

    accuracy                           1.00     56962
   macro avg       0.97      0.91      0.94     56962
weighted avg       1.00      1.00      1.00     56962
```

5.1 Accuracy: 0.9996

- This looks **extremely high**, but remember your dataset is **highly imbalanced**:
  - 0 → non-fraud (majority class)
  - 1 → fraud (minority class)
- Accuracy mostly reflects **correctly predicting non-fraud transactions.**
- High accuracy doesn't mean the model is perfect for fraud detection — focus on **precision, recall, F1-score** for the fraud class.

5.2 Precision, Recall, F1-Score

- **Precision (fraud)** = 0.94 → Out of all transactions predicted as fraud, 94% were actually fraud.
- **Recall (fraud)** = 0.82 → Out of all actual fraud transactions, 82% were correctly detected.
- **F1-score** = 0.87 → Harmonic mean of precision and recall → good balance.

  In real fraud detection, **recall is very important** because missing a fraud (false negative) can be costly.

5.3 Next Steps to Improve Optional (model is already strong)

1. **Handle Imbalance:**

- Use `class_weight='balanced'` in RandomForest:

```
model = RandomForestClassifier(n_estimators=100, random_state=42, class_weight='balanced', n_j
```

- Or use SMOTE (Synthetic Minority Oversampling Technique) to oversample fraud cases.

2. **Tune Hyperparameters:**

- Increase n_estimators, adjust max_depth, min_samples_split to improve recall.

3. **Try Other Models:**

- XGBoost, LightGBM → often give **better recall for imbalanced datasets.**

6 Save Model for App

- Saves the model so we can load it in Streamlit app without retraining every time.

[15]:
```
import pickle

# Save trained model
pickle.dump(model, open("model.pkl", "wb"))
```

7 Create Streamlit App

- Takes user input for features → predicts fraud.
- `model.pkl` is loaded and used for prediction.
- You can expand inputs to **all important features**.

```python
import streamlit as st
import pandas as pd
import numpy as np
import pickle

# ---------------------------
# Load Model and Dataset
# ---------------------------
model = pickle.load(open("model.pkl", "rb"))
data = pd.read_csv("data/creditcard.csv")

st.set_page_config(page_title="Credit Card Fraud Detection", layout="wide")
st.title("  Credit Card Fraud Detection")
st.write("This app predicts whether a credit card transaction is fraudulent or not.")

# ---------------------------
# Sidebar for User Input
# ---------------------------
st.sidebar.header("Choose Input Method")
input_method = st.sidebar.radio("Select input type:", ["Sample Transaction", "Manual Input", "

# ---------------------------
# Option 1: Sample Transaction
# ---------------------------
if input_method == "Sample Transaction":
    st.subheader("Select a Sample Transaction")

    # Select 1 random fraud
    fraud_sample = data[data['Class']==1].sample(1)

    # Select 4 random non-fraud
    nonfraud_sample = data[data['Class']==0].sample(4)

    # Combine and shuffle
    sample_rows = pd.concat([fraud_sample, nonfraud_sample]).sample(frac=1)

    # Create friendly labels (show Fraud / Not Fraud)
    row_labels = [f"Index {i} - {'Fraud' if row['Class']==1 else 'Not Fraud'}" for i, row in sa

    selected_label = st.selectbox("Choose a sample row:", row_labels)
    selected_index = int(selected_label.split()[1])
    selected_row = data.loc[selected_index]
    features = selected_row.drop("Class").values.reshape(1, -1)

# ---------------------------
# Option 2: Manual Input
# ---------------------------
elif input_method == "Manual Input":
```

```python
    st.subheader("Enter Transaction Details Manually")
    input_dict = {}
    input_dict["Time"] = st.number_input("Time", value=float(data["Time"].mean()))
    for col in [f"V{i}" for i in range(1,29)]:
        input_dict[col] = st.number_input(col, value=float(data[col].mean()))
    input_dict["Amount"] = st.number_input("Amount", value=float(data["Amount"].mean()))
    features = np.array([list(input_dict.values())])

# ---------------------------
# Option 3: Index Lookup
# ---------------------------
else:
    st.subheader("Check any transaction by Index")
    idx = st.number_input("Enter Index (0 to {})".format(len(data)-1), min_value=0, max_value=
    selected_row = data.loc[int(idx)]
    features = selected_row.drop("Class").values.reshape(1, -1)
    st.write(f"Actual Class: {'Fraud' if selected_row['Class']==1 else 'Not Fraud'}")

# ---------------------------
# Prediction
# ---------------------------
if st.button("Predict"):
    prediction = model.predict(features)
    prediction_proba = model.predict_proba(features)[0][1]

    st.write("## Prediction Result:")
    if prediction[0] == 1:
        st.error(f"  Fraudulent Transaction detected! Probability: {prediction_proba:.2f}")
    else:
        st.success(f"  Not Fraudulent. Probability of fraud: {prediction_proba:.2f}")

# ---------------------------
# Detailed Explanation at Bottom
# ---------------------------
st.markdown("---")
st.markdown("""
**About this App:**

1  **Index**
- This is the row number in  dataset (`data.csv`).
- Example: `Index 43428` means this transaction is at row 43428.
- Helps  identify the transaction being tested.

2  **Class**
- Class is the actual label in the dataset:
  - 0 → Not Fraudulent
  - 1 → Fraudulent
- Example: `Class 1.0` means the transaction is actually a fraud.
```

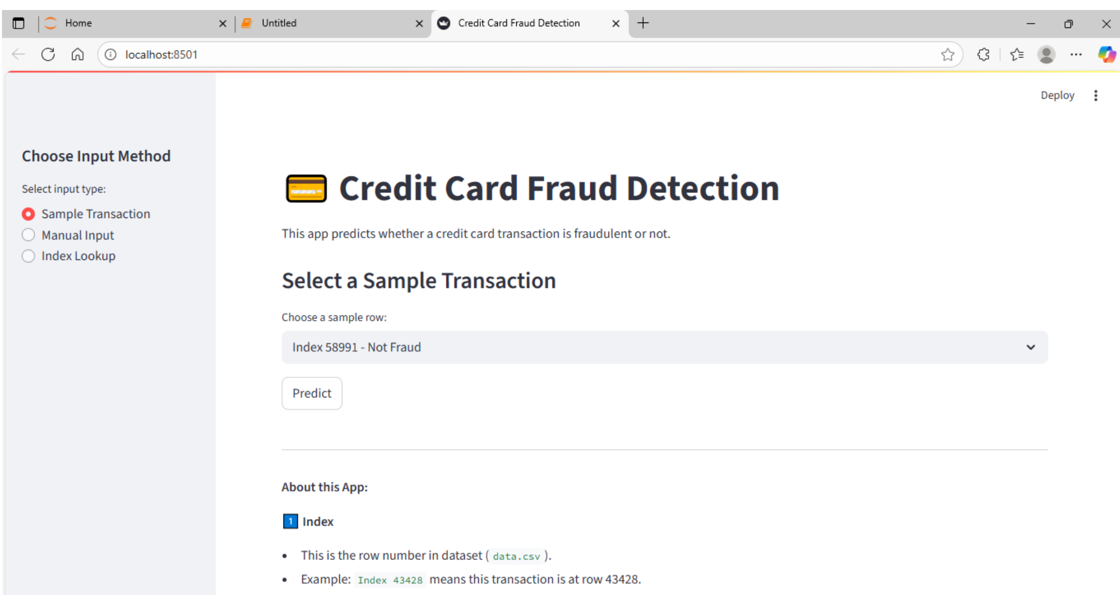
```
3 **Why show Index and Class?**
- The dropdown shows 5 sample transactions from the dataset.
- Displaying `Index ... - Class ...` makes it clear which transaction is fraud or non-fraud be
- Helps you test if the model prediction matches the actual label.

 **In short:**
`Index 43428 - Class 1.0` → Transaction at row 43428 is actually fraud in the dataset.

- You can either select **sample transactions**, enter **all 30 features manually**, or **looku
- Designed for portfolio showcase: interactive, professional, and easy to test.
""")
```

Run app: >

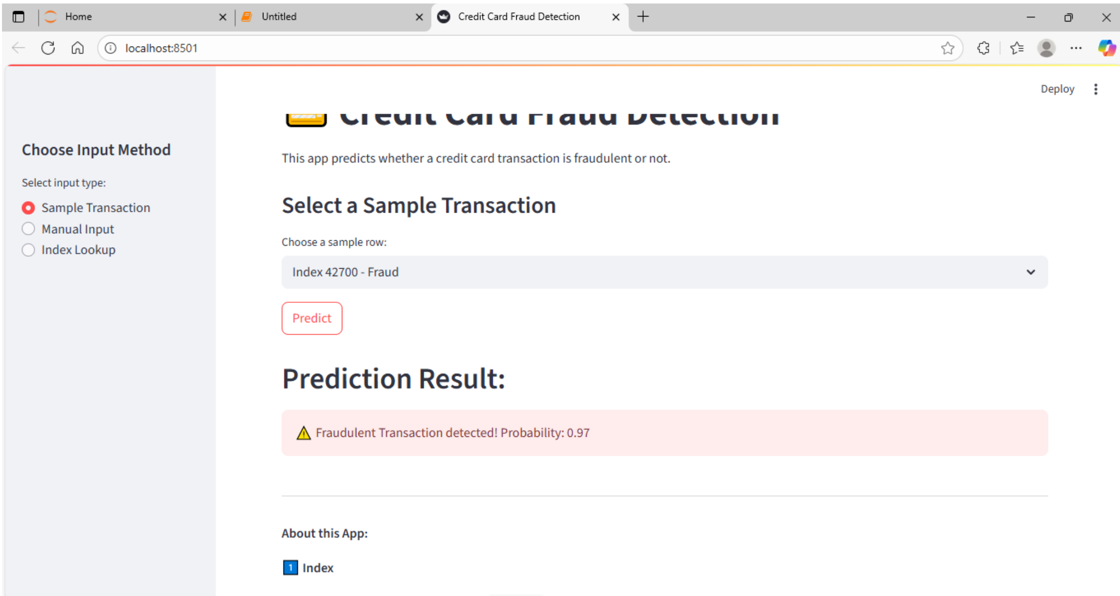
```
streamlit run app.py
```

App Preview: Credit Card Fraud Detection Here are some screenshots showing how the app looks and works:

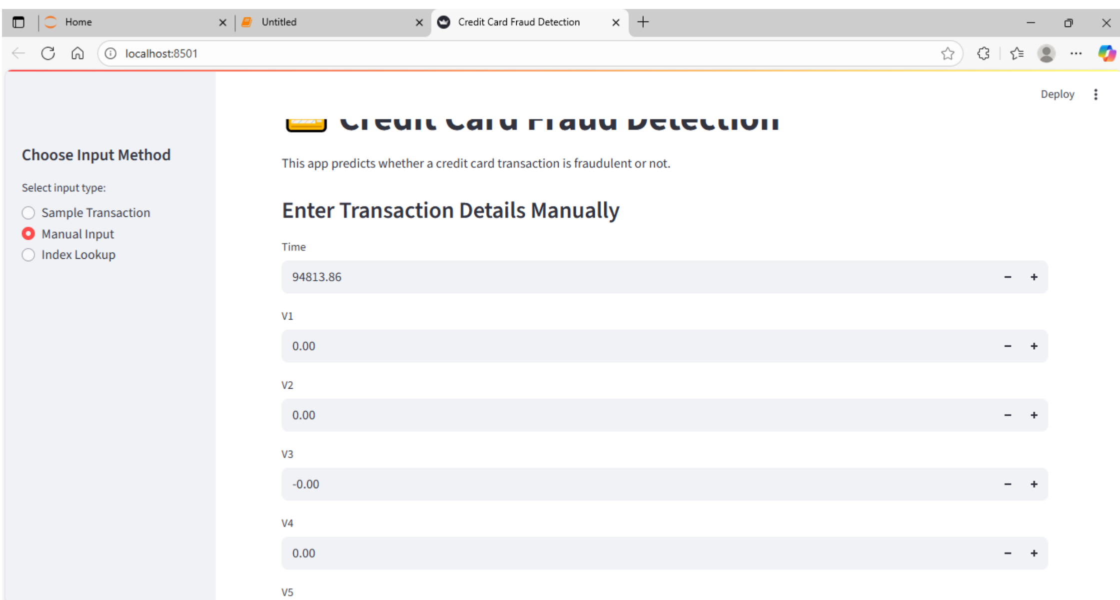
8 App Overview



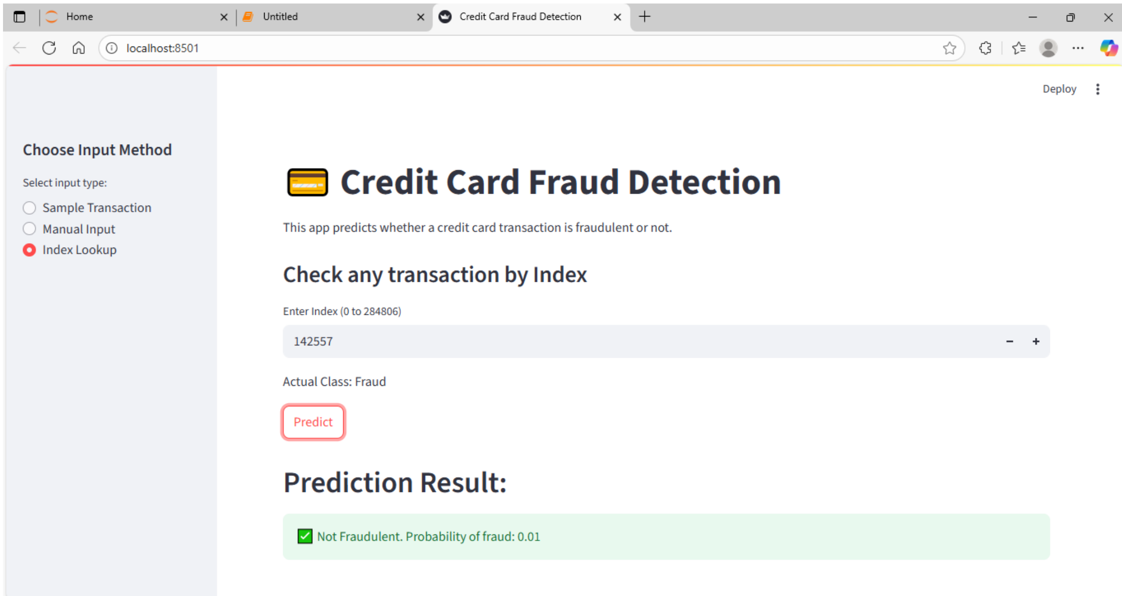
9 Sample Transaction



10 Manual Input



11 Index Lookup



12 Conclusion

- The **Random Forest Classifier** can detect fraudulent transactions with high accuracy.
- The **interactive Streamlit app** allows users to test the model using:
  - Sample transactions
  - Manual input
  - Index lookup

12.1 Notes / Next Steps

- Future improvements:
  - Add **feature importance visualization**
  - Deploy app online using **Streamlit Cloud or Heroku**
  - Extend to **other machine learning models** for comparison