Predicting Health Insurance Fraud Using Machine Learning

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I. Introduction

Healthcare fraud is a pervasive issue that has significant financial, ethical, and operational implications, affecting government programs, insurance companies, healthcare providers, and patients alike. Fraudulent activities in healthcare result in billions of dollars in financial losses annually, placing a burden on both public and private insurers while increasing overall healthcare costs. The **National Health Care Anti-Fraud Association (NHCAA)** estimates that healthcare fraud costs the United States **tens of billions of dollars each year**, affecting the efficiency and sustainability of healthcare programs.

Fraud in health insurance can manifest in various forms, including **phantom billing** (charging for services never provided), **upcoding** (billing for more expensive procedures than those performed), **unbundling** (separating services that should be billed together), **duplicate billing**, and **identity fraud**. These fraudulent activities exploit loopholes in the billing system, making them difficult to detect through traditional rule-based fraud detection techniques. Most existing fraud detection methods rely on manual audits, predefined rules, and expert-based reviews, which are labor-intensive, time-consuming, and ineffective against evolving fraudulent schemes.

Machine learning (ML) and data-driven analytics have emerged as effective solutions for fraud detection in healthcare by leveraging large datasets to identify patterns indicative of fraudulent behavior. Unlike static rule-based systems, ML models can dynamically analyze vast amounts of healthcare claims data, recognize hidden anomalies, and detect fraud more accurately over time. ML-based fraud detection systems also reduce false positives, allowing investigators to focus on high-risk claims while minimizing disruptions for legitimate providers.

This project aims to build a **robust fraud detection model** that can accurately distinguish fraudulent from non-fraudulent claims using a **combination of supervised and unsupervised machine learning techniques**. The analysis will be conducted using **three key datasets**:

- **CMS Medicare Data** – A large dataset of Medicare claims providing insight into billing practices.
- **Kaggle Healthcare Fraud Dataset** – A labeled dataset containing known cases of fraudulent providers.
- **Synthea Synthetic Data** – A simulated dataset modeling real-world healthcare scenarios to enhance training and testing.

By integrating these datasets, we aim to develop an **intelligent fraud detection system** that utilizes **statistical learning techniques from An Introduction to Statistical Learning (ISL)** to enhance fraud identification. The results of this study will contribute to more effective fraud prevention strategies, reducing financial losses and improving healthcare system integrity.

II. Schedule

We structured our project timeline into weekly milestones to ensure timely and systematic progress. The original plan allocated specific tasks to each member, with an emphasis on collaboration during analysis and documentation.

1. Completed Tasks (Weeks 1–6)

Week	Tasks Completed	Notes
Week 1–2	Data collection from CMS, Kaggle, Synthea	All datasets successfully downloaded, loaded, and organized into dictionaries by source.
Week 3–4	Data cleaning & preprocessing	CMS, Kaggle, and Synthea data cleaned. Missing values handled, irrelevant columns dropped, outliers capped.
Week 5	Exploratory Data Analysis (EDA)	Visualized key variables for all datasets (e.g., gender, income, charges, fraud status). Class imbalance confirmed.
Week 6	Descriptive statistics	Variable distributions examined and summarized for the report.

2. Upcoming Tasks (Weeks 7–12)

Week	Task	Assigned Member(s)
Week 7	Merge inpatient/outpatient data (Kaggle); begin feature engineering	Nhan
Week 8	Model development: logistic regression, decision tree, random forest	Tan
Week 9	Advanced models: SVM, XGBoost, clustering	Tan
Week 10	SHAP analysis, performance evaluation	Tan, Nhan
Week 11	Report writing, citation finalization	Andre
Week 12	Report finalization and presentation prep	All Members

3. Deviations from the Original Plan

- Originally, feature engineering was scheduled for Weeks 3–4. However, we postponed this task to **Week 7** in order to complete a more thorough EDA and data cleaning process, especially across three large datasets.
- This change ensures that models are built on high-quality, consistent inputs and supports better feature selection based on actual data patterns.

4. Overall Status

We are **on track** with the revised schedule. All foundational tasks (cleaning, EDA, visualization) have been completed. The team is ready to begin modeling and performance evaluation in the next phase.

III. Completed Tasks and Result

In [163…

```
# Basic Data Handling
import pandas as pd
import numpy as np
import os # Used for navigating folders, listing files, creating/deleting folders

# Visualization Libraries
import matplotlib.pyplot as plt
import seaborn as sns

# Data Preprocessing & Machine Learning Tools
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer

# Handling Imbalanced Datasets
# SMOTE = Synthetic Minority Over-sampling Technique
# This helps generate synthetic data for the minority class (e.g., fraud cases)
# Useful when the dataset is imbalanced (few fraudulent cases vs. many non-fraud)
from imblearn.over_sampling import SMOTE
```

In [164…

```
# Warnings and Plot Settings
import warnings
warnings.filterwarnings('ignore')

# Plot Styles
sns.set(style='whitegrid')
plt.rcParams['figure.figsize'] = (7, 5)
```

1. Organize and Load Data

We Organize and Load Data Using Folder-Wise Dictionaries In this project, we work with three distinct datasets:

- **CMS Medicare billing data**
- **Kaggle healthcare fraud data**
- **Synthea synthetic health records**

Each of these data sources includes multiple CSV files representing different aspects of healthcare data (e.g., patient records, procedures, claims, and providers). To ensure a clean, scalable, and maintainable workflow, we organize the data using the following strategy:

Folder-Wise Data Storage: We place the CSV files into separate folders based on their source:

- CMS
- Kaggle
- Synthea

This will helps to keep files organized and avoids confusion, simplifies access when working with multiple files and prevents naming conflicts between datasets with similar file names.

In [166…

```
# Root folder where all subfolders live
root = "C:\\Users\\nhanf\\OneDrive\\Máy tính\\Machine Learning 4419"
```

```
# Names of subfolders
subfolders = ['CMS', 'Kaggle', 'Synthea']

# Master dictionary to store datasets
all_data = {}

# Loop through each subfolder
for subfolder in subfolders:
    folder_path = os.path.join(root, subfolder)
    dataset_dict = {}
    for filename in os.listdir(folder_path):
        if filename.endswith(".csv"):
            file_path = os.path.join(folder_path, filename)
            df_name = filename.replace(".csv", "")
            dataset_dict[df_name] = pd.read_csv(file_path)
            print(f"✅ Loaded {df_name} from {subfolder}")
    all_data[subfolder] = dataset_dict
```

```
✅ Loaded MUP_PHY_R24_P05_V10_D22_Geo from CMS
✅ Loaded Test-1542969243754 from Kaggle
✅ Loaded Test_Beneficiarydata-1542969243754 from Kaggle
✅ Loaded Test_Inpatientdata-1542969243754 from Kaggle
✅ Loaded Test_Outpatientdata-1542969243754 from Kaggle
✅ Loaded Train-1542865627584 from Kaggle
✅ Loaded Train_Beneficiarydata-1542865627584 from Kaggle
✅ Loaded Train_Inpatientdata-1542865627584 from Kaggle
✅ Loaded Train_Outpatientdata-1542865627584 from Kaggle
✅ Loaded allergies from Synthea
✅ Loaded careplans from Synthea
✅ Loaded claims from Synthea
✅ Loaded claims_transactions from Synthea
✅ Loaded conditions from Synthea
✅ Loaded devices from Synthea
✅ Loaded encounters from Synthea
✅ Loaded imaging_studies from Synthea
✅ Loaded immunizations from Synthea
✅ Loaded medications from Synthea
✅ Loaded observations from Synthea
✅ Loaded organizations from Synthea
✅ Loaded patients from Synthea
✅ Loaded payers from Synthea
✅ Loaded payer_transitions from Synthea
✅ Loaded procedures from Synthea
✅ Loaded providers from Synthea
✅ Loaded supplies from Synthea
```

2. CMS Medicare Dataset: Analysis, Visualization, and Preprocessing

In [168…

```
# Access CMS dataset from the organized data dictionary
cms_df = all_data['CMS']['MUP_PHY_R24_P05_V10_D22_Geo']

# Preview the data
cms_df.head()
```

Out[168...

	Rndrng_Prvdr_Geo_Lvl	Rndrng_Prvdr_Geo_Cd	Rndrng_Prvdr_Geo_Desc	HCPCS_Cd	HCPCS_Desc	H
0	National	NaN	National	0001A	Intramuscular administration of single severe ...	
1	National	NaN	National	0001A	Intramuscular administration of single severe ...	
2	National	NaN	National	0001U	Red blood cell typing	
3	National	NaN	National	0002A	Intramuscular administration of single severe ...	
4	National	NaN	National	0002A	Intramuscular administration of single severe ...	

2.1 Check Data Types & Structure

In [170...

```
# Check the shape and column of the DataFrame
cms_df.info()  # Includes shape, column names, and data types
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 270673 entries, 0 to 270672
Data columns (total 15 columns):
 #   Column                 Non-Null Count   Dtype  
---  ------                 --------------   -----  
 0   Rndrng_Prvdr_Geo_Lvl   270673 non-null  object 
 1   Rndrng_Prvdr_Geo_Cd    257348 non-null  object 
 2   Rndrng_Prvdr_Geo_Desc  270670 non-null  object 
 3   HCPCS_Cd               270673 non-null  object 
 4   HCPCS_Desc             270673 non-null  object 
 5   HCPCS_Drug_Ind         270673 non-null  object 
 6   Place_Of_Srvc          270673 non-null  object 
 7   Tot_Rndrng_Prvdrs      270673 non-null  int64  
 8   Tot_Benes              270673 non-null  int64  
 9   Tot_Srvcs              270673 non-null  float64
 10  Tot_Bene_Day_Srvcs     270673 non-null  int64  
 11  Avg_Sbmtd_Chrg         270673 non-null  float64
 12  Avg_Mdcr_Alowd_Amt     270673 non-null  float64
 13  Avg_Mdcr_Pymt_Amt      270673 non-null  float64
 14  Avg_Mdcr_Stdzd_Amt     270673 non-null  float64
dtypes: float64(5), int64(3), object(7)
memory usage: 31.0+ MB
```

In [171...

```
# Show data types of all columns
cms_df.dtypes
```

Out[171…
```
Rndrng_Prvdr_Geo_Lvl       object
Rndrng_Prvdr_Geo_Cd        object
Rndrng_Prvdr_Geo_Desc      object
HCPCS_Cd                   object
HCPCS_Desc                 object
HCPCS_Drug_Ind             object
Place_Of_Srvc              object
Tot_Rndrng_Prvdrs           int64
Tot_Benes                   int64
Tot_Srvcs                 float64
Tot_Bene_Day_Srvcs          int64
Avg_Sbmtd_Chrg            float64
Avg_Mdcr_Alowd_Amt        float64
Avg_Mdcr_Pymt_Amt         float64
Avg_Mdcr_Stdzd_Amt        float64
dtype: object
```

2.2 Check for Missing Values

In [173…
```
# Count missing values per column
missing_counts = cms_df.isnull().sum()
missing_percent = (missing_counts / len(cms_df)) * 100

# Show only columns with missing data
missing_summary = pd.DataFrame({
    'Missing Values': missing_counts,
    'Percent Missing': missing_percent
})
missing_summary = missing_summary[missing_summary['Missing Values'] > 0]
missing_summary.sort_values(by='Percent Missing', ascending=False)
```

Out[173…

	Missing Values	Percent Missing
Rndrng_Prvdr_Geo_Cd	13325	4.922914
Rndrng_Prvdr_Geo_Desc	3	0.001108

2.3 CMS Data Preprocessing

In [175…
```
# Show missing values again (recap)
cms_df.isnull().sum().sort_values(ascending=False).head(10)
```

Out[175…
```
Rndrng_Prvdr_Geo_Cd      13325
Rndrng_Prvdr_Geo_Desc        3
Rndrng_Prvdr_Geo_Lvl         0
HCPCS_Cd                     0
HCPCS_Desc                   0
HCPCS_Drug_Ind               0
Place_Of_Srvc                0
Tot_Rndrng_Prvdrs            0
Tot_Benes                    0
Tot_Srvcs                    0
dtype: int64
```

We treat **Rndrng_Prvdr_Geo_Cd** as categorical string and fill with 'Unknown'.

In [177…
```
# Convert Rndrng_Prvdr_Geo_Cd (FIPS code) to string so it can be treated as a categorical var
cms_df['Rndrng_Prvdr_Geo_Cd'] = cms_df['Rndrng_Prvdr_Geo_Cd'].astype(str)
```

```
# Fill missing FIPS codes with 'Unknown' to preserve rows and treat them as a separate catego
cms_df['Rndrng_Prvdr_Geo_Cd'].fillna('Unknown', inplace=True)

# Fill missing state names (Rndrng_Prvdr_Geo_Desc) with 'Unknown' to avoid dropping rows duri
cms_df['Rndrng_Prvdr_Geo_Desc'].fillna('Unknown', inplace=True)
```

Handling Outliers in Submitted Charges

The *Avg_Sbmtd_Chrg* column in the CMS dataset represents the average submitted charge for a medical service by providers. A boxplot analysis revealed that this variable contains **significant outliers**, with a small number of records showing extremely high charges (some exceeding $100,000), while the majority of data points are concentrated near zero.

To ensure clearer visualizations and more stable statistical models, we applied a **capping strategy** using the **99th percentile (Winsorization)**. This method preserves most of the distribution while preventing a small number of extreme values from dominating charts and skewing metrics like the mean and standard deviation.

We created a new column, *Avg_Sbmtd_Chrg_Capped*, for use in visualizations and modeling. This ensures we retain the original values for reference while using the capped version for analysis.

In [179…

```
# Cap Avg_Sbmtd_Chrg at 99th percentile to reduce impact of extreme outliers
cap_value = cms_df['Avg_Sbmtd_Chrg'].quantile(0.99)
cms_df['Avg_Sbmtd_Chrg_Capped'] = cms_df['Avg_Sbmtd_Chrg'].apply(lambda x: min(x, cap_value))
```

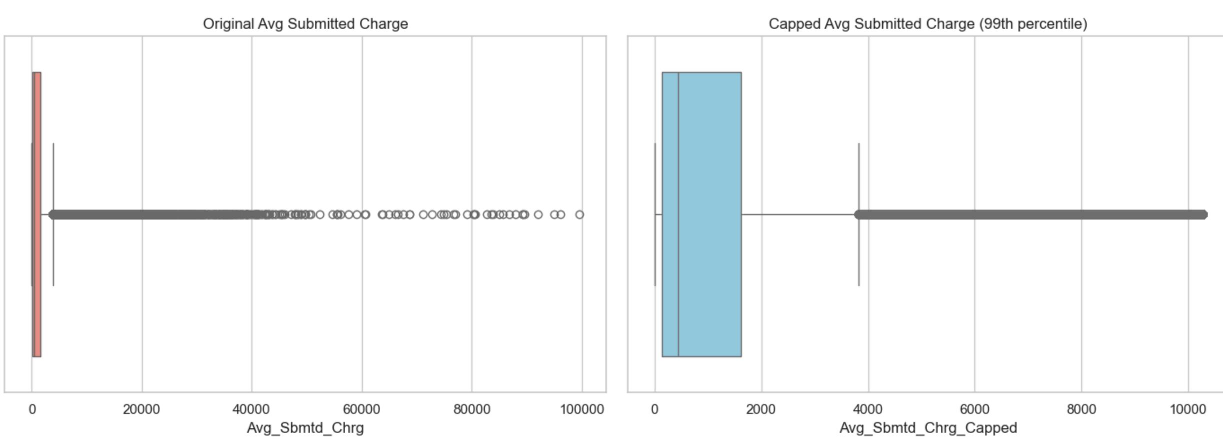
In [180…

```
fig, axs = plt.subplots(1, 2, figsize=(14, 5))

# Original
sns.boxplot(x=cms_df['Avg_Sbmtd_Chrg'], ax=axs[0], color='salmon')
axs[0].set_title('Original Avg Submitted Charge')

# Capped
sns.boxplot(x=cms_df['Avg_Sbmtd_Chrg_Capped'], ax=axs[1], color='skyblue')
axs[1].set_title('Capped Avg Submitted Charge (99th percentile)')

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



2.4 Describe the statistics of the data variables

In [182…

```
# Display descriptive statistics for key numeric columns
cms_df[['Tot_Srvcs', 'Tot_Rndrng_Prvdrs', 'Tot_Benes',
```

```
        'Avg_Sbmtd_Chrg', 'Avg_Mdcr_Pymt_Amt', 'Avg_Mdcr_Stdzd_Amt']].describe().T
```

Out[182…

	count	mean	std	min	25%	50%	
Tot_Srvcs	270673.0	23594.607828	618354.228806	11.000000	40.000000	162.000000	1102.
Tot_Rndrng_Prvdrs	270673.0	266.753924	3279.531740	1.000000	11.000000	29.000000	95.
Tot_Benes	270673.0	5342.793747	110063.595958	11.000000	30.000000	106.000000	586.
Avg_Sbmtd_Chrg	270673.0	1309.701656	2525.174026	0.000103	127.039817	440.559240	1606.
Avg_Mdcr_Pymt_Amt	270673.0	232.247881	644.535722	0.000000	27.780595	85.518203	250.
Avg_Mdcr_Stdzd_Amt	270673.0	230.059629	640.828785	0.000079	27.596064	85.034015	249.

Descriptive Statistics of Key CMS Variables We examined the main numerical variables in the CMS dataset. The results from .describe() show the following patterns:

- **Tot_Srvcs** (Total Services):

  Ranges from a minimum of 1 to a maximum of over 2 million, with a mean around 7600.

  Indicates huge variation in how often different services are billed.

- **Tot_Benes** (Number of Beneficiaries):

  Shows a similar trend — a few services reach a large Medicare population, while most serve very few.

- **Avg_Sbmtd_Chrg** (Submitted Charges):

  Highly skewed to the right, with a median much lower than the mean, confirming the presence of extreme outliers.

  Min charge is near 0. While max reaches 100,000+, though 99% of values are below $10,000.

- **Avg_Mdcr_Pymt_Amt** (Amount Medicare Paid):

  Closely follows the same pattern as submitted charge but generally lower (as Medicare doesn't pay full charge).

  This can reveal gaps between billed and approved amounts — possibly indicating upcoding or overbilling.

- **Tot_Rndrng_Prvdrs** (Number of Rendering Providers):

  Averages suggest most services are offered by a limited number of providers, while a few procedures are performed by many.

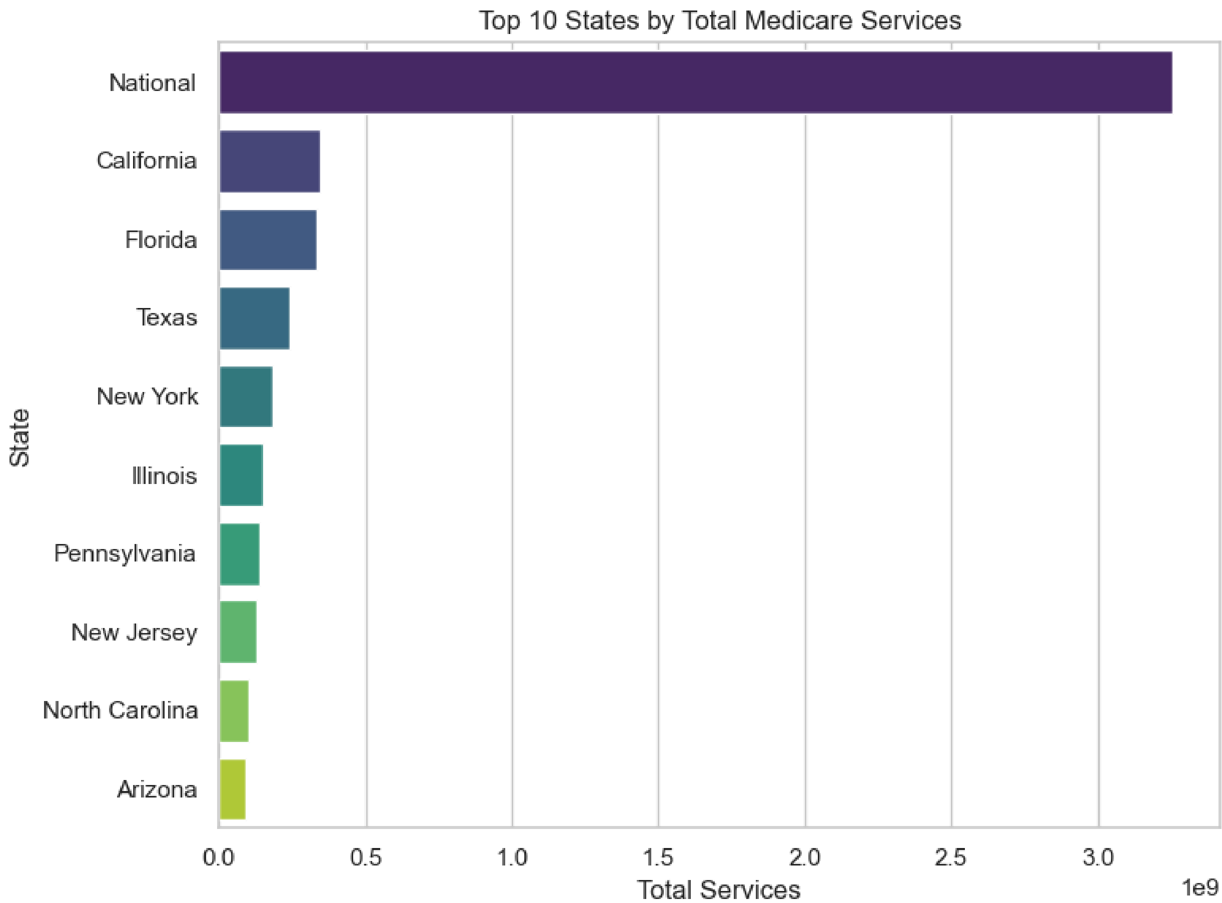
2.5 Data Visualized

2.5.1 Total Services by State

In [185…

```
# Top 10 states by total services
top_states = cms_df.groupby('Rndrng_Prvdr_Geo_Desc')['Tot_Srvcs'].sum().sort_values(ascending
```

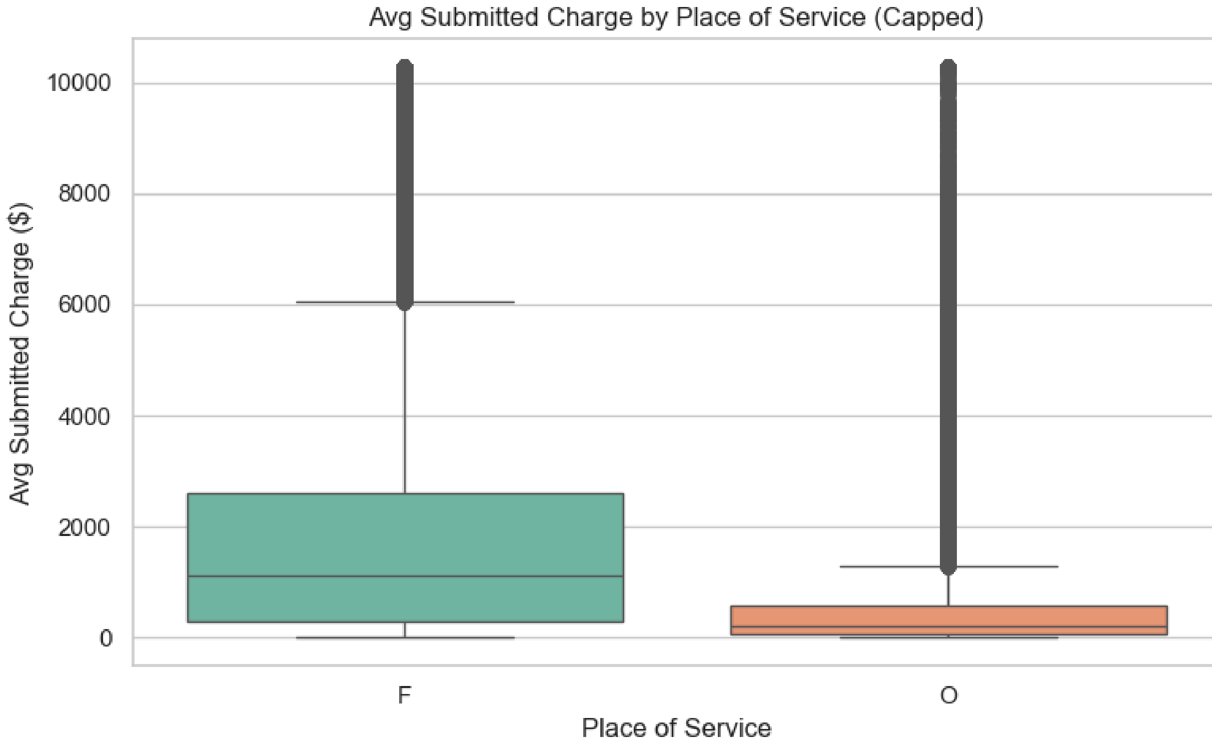
```
plt.figure(figsize=(8, 6))
sns.barplot(x=top_states.values, y=top_states.index, palette="viridis")
plt.title('Top 10 States by Total Medicare Services')
plt.xlabel('Total Services')
plt.ylabel('State')
plt.tight_layout()
plt.show()
```



2.5.2 Avg Submitted Charge by Place of Service

In [187…

```
plt.figure(figsize=(8, 5))
sns.boxplot(data=cms_df, x='Place_Of_Srvc', y='Avg_Sbmtd_Chrg_Capped', palette="Set2")
plt.title('Avg Submitted Charge by Place of Service (Capped)')
plt.xlabel('Place of Service')
plt.ylabel('Avg Submitted Charge ($)')
plt.tight_layout()
plt.show()
# Identifies whether the place of service submitted on the claims is a facility (value of 'F'
```



The CMS dataset contains both numerical and categorical variables. Key categorical variables include geographic indicators (**Rndrng_Prvdr_Geo_Lvl**, **Rndrng_Prvdr_Geo_Desc**, **Place_Of_Srvc**) and service identifiers (**HCPCS_Cd**). Numerical variables such as **Tot_Srvcs**, **Avg_Sbmtd_Chrg**, and **Avg_Mdcr_Pymt_Amt** represent service volume and financial data. Missing values are minimal and mostly found in drug indicator or geographic labels, and will be handled using imputation or by dropping if appropriate.

3. Kaggle Dataset: Analysis, Visualization, and Preprocessing

3.1 Load the data from the dictionary

In [211…

```
# Load the main training dataset (has fraud labels)
kaggle_train_df = all_data['Kaggle']['Train-1542865627584']

# Preview the data
kaggle_train_df.head()
```

Out[211…

	Provider	PotentialFraud
0	PRV51001	No
1	PRV51003	Yes
2	PRV51004	No
3	PRV51005	Yes
4	PRV51007	No

3.2 Check Data Types & Structure

In [220…

```
# Check shape and structure
kaggle_train_df.info()

# Quick summary of all column names and types
kaggle_train_df.dtypes
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5410 entries, 0 to 5409
Data columns (total 2 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   Provider        5410 non-null   object
 1   PotentialFraud  5410 non-null   object
dtypes: object(2)
memory usage: 84.7+ KB
```

Out[220…

```
Provider          object
PotentialFraud    object
dtype: object
```

3.3 Check for Missing Values

The primary Kaggle training file (`Train-1542865627584.csv`) contains 5,410 records and 2 columns:

- `Provider` : a unique identifier for each healthcare provider
- `PotentialFraud` : the target variable indicating suspected fraudulent activity

No missing values were found in this file, and both columns are of type `object` . No data cleaning is needed at this stage, though `PotentialFraud` will later be encoded as a binary variable (`1 = Fraud` , `0 = Not Fraud`) for modeling.

3.4 Basic Statistics

In [226…

```
# Check class distribution
kaggle_train_df['PotentialFraud'].value_counts()
```

Out[226…

```
PotentialFraud
No     4904
Yes     506
Name: count, dtype: int64
```

To better understand the distribution of our target variable, we examined the frequency of `PotentialFraud` values. This variable is binary and identifies whether each provider is potentially involved in fraudulent activities.

Out of **5,410 total providers**:

- **4,904** are labeled as **"No"** (not fraudulent)
- **506** are labeled as **"Yes"** (potential fraud)

This reveals a clear **class imbalance**, with only **~9.4%** of providers flagged as potentially fraudulent.

Such imbalance is common in fraud detection tasks and has important implications:

- Predictive models trained on imbalanced data tend to favor the majority class ("No")
- Specialized techniques like **SMOTE (Synthetic Minority Over-sampling Technique)** or **undersampling** may be needed during model training

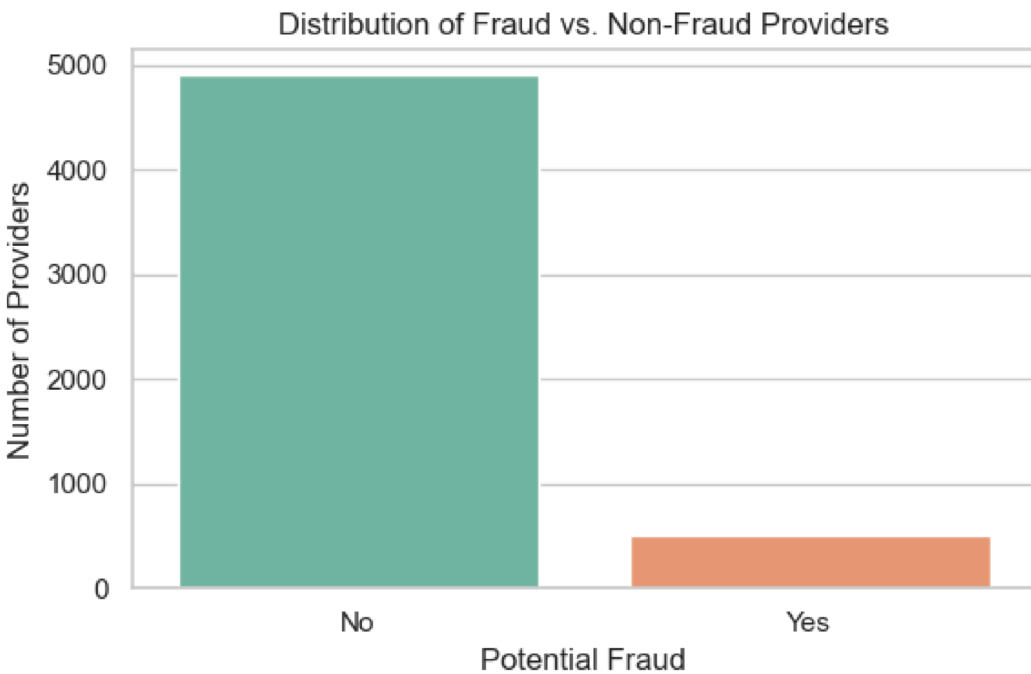
- Evaluation metrics must go beyond simple accuracy and include **precision, recall, F1-score**, and **AUC**

Visualizing this distribution confirms the imbalance and helps us prepare for modeling decisions later.

3.5 Kaggle Data Visualized

In [230…

```
# Plot the distribution of the target variable
plt.figure(figsize=(6, 4))
sns.barplot(
    x=kaggle_train_df['PotentialFraud'].value_counts().index,
    y=kaggle_train_df['PotentialFraud'].value_counts().values,
    palette="Set2"
)
plt.title('Distribution of Fraud vs. Non-Fraud Providers')
plt.xlabel('Potential Fraud')
plt.ylabel('Number of Providers')
plt.tight_layout()
plt.show()
```



As shown in the bar chart above, the `PotentialFraud` variable is highly imbalanced. Fraudulent cases ("Yes") make up less than 10% of the data.

This imbalance confirms the need for proper data balancing techniques in our modeling phase, such as **SMOTE**, **undersampling**, or using **stratified sampling** when splitting the dataset.

4. Synthea Dataset: Analysis, Visualization, and Preprocessing

Synthea consists of multiple CSVs, we'll treat this step as exploring the main data tables (e.g., patients.csv) first.

4.1 Load patients.csv from Dictionary

In [238…

```
synthea_patients_df = all_data['Synthea']['patients']
synthea_patients_df.head()
```

Out[238…

	Id	BIRTHDATE	DEATHDATE	SSN	DRIVERS	PASSPORT	PREFIX	FIRST	MII
0	30a6452c-4297-a1ac-977a-6a23237c7b46	1994-02-06	NaN	999-52-8591	S99996852	X47758697X	Mr.	Joshua658	Al
1	34a4dcc4-35fb-6ad5-ab98-be285c586a4f	1968-08-06	2009-12-11	999-75-3953	S99993577	X28173268X	Mr.	Bennie663	
2	7179458e-d6e3-c723-2530-d4acfe1c2668	2008-12-21	NaN	999-70-1925	NaN	NaN	NaN	Hunter736	Mckinle
3	37c177ea-4398-fb7a-29fa-70eb3d673876	1994-01-27	NaN	999-27-9779	S99995100	X83694889X	Mrs.	Carlyn477	Florenci
4	0fef2411-21f0-a269-82fb-c42b55471405	2019-07-27	NaN	999-50-8977	NaN	NaN	NaN	Robin66	Jeram

5 rows × 28 columns

4.2 Check Structure & Data Types

In [243…

```
# Basic structure and data types
synthea_patients_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 106 entries, 0 to 105
Data columns (total 28 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   Id                   106 non-null    object 
 1   BIRTHDATE            106 non-null    object 
 2   DEATHDATE            6 non-null      object 
 3   SSN                  106 non-null    object 
 4   DRIVERS              84 non-null     object 
 5   PASSPORT             75 non-null     object 
 6   PREFIX               79 non-null     object 
 7   FIRST                106 non-null    object 
 8   MIDDLE               89 non-null     object 
 9   LAST                 106 non-null    object 
 10  SUFFIX               0 non-null      float64
 11  MAIDEN               28 non-null     object 
 12  MARITAL              64 non-null     object 
 13  RACE                 106 non-null    object 
 14  ETHNICITY            106 non-null    object 
 15  GENDER               106 non-null    object 
 16  BIRTHPLACE           106 non-null    object 
 17  ADDRESS              106 non-null    object 
 18  CITY                 106 non-null    object 
 19  STATE                106 non-null    object 
 20  COUNTY               106 non-null    object 
 21  FIPS                 71 non-null     float64
 22  ZIP                  106 non-null    int64  
 23  LAT                  106 non-null    float64
 24  LON                  106 non-null    float64
 25  HEALTHCARE_EXPENSES  106 non-null    float64
 26  HEALTHCARE_COVERAGE  106 non-null    float64
 27  INCOME               106 non-null    int64  
dtypes: float64(6), int64(2), object(20)
memory usage: 23.3+ KB
```

In [245…

```
# Data types summary
synthea_patients_df.dtypes
```

Out[245…

```
Id                       object
BIRTHDATE                object
DEATHDATE                object
SSN                      object
DRIVERS                  object
PASSPORT                 object
PREFIX                   object
FIRST                    object
MIDDLE                   object
LAST                     object
SUFFIX                  float64
MAIDEN                   object
MARITAL                  object
RACE                     object
ETHNICITY                object
GENDER                   object
BIRTHPLACE               object
ADDRESS                  object
CITY                     object
STATE                    object
COUNTY                   object
FIPS                    float64
ZIP                       int64
LAT                     float64
LON                     float64
HEALTHCARE_EXPENSES     float64
HEALTHCARE_COVERAGE     float64
INCOME                    int64
dtype: object
```

4.3 Check for Missing Values

In [247…

```python
# Count and percentage of missing values
missing_counts = synthea_patients_df.isnull().sum()
missing_percent = (missing_counts / len(synthea_patients_df)) * 100

missing_summary = pd.DataFrame({
    'Missing Values': missing_counts,
    'Percent Missing': missing_percent
}).query('`Missing Values` > 0').sort_values('Percent Missing', ascending=False)

missing_summary
```

Out[247...

	Missing Values	Percent Missing
SUFFIX	106	100.000000
DEATHDATE	100	94.339623
MAIDEN	78	73.584906
MARITAL	42	39.622642
FIPS	35	33.018868
PASSPORT	31	29.245283
PREFIX	27	25.471698
DRIVERS	22	20.754717
MIDDLE	17	16.037736

4.4 Data Preprocessing

In [260...

```
# Drop columns only if they exist in the DataFrame
drop_cols = ['SUFFIX', 'MAIDEN', 'PASSPORT', 'PREFIX', 'DRIVERS', 'MIDDLE']
synthea_patients_df.drop(columns=drop_cols, errors='ignore', inplace=True)
```

In [258...

```
synthea_patients_df.columns.tolist()
```

Out[258...

```
['Id',
 'BIRTHDATE',
 'DEATHDATE',
 'SSN',
 'FIRST',
 'LAST',
 'MARITAL',
 'RACE',
 'ETHNICITY',
 'GENDER',
 'BIRTHPLACE',
 'ADDRESS',
 'CITY',
 'STATE',
 'COUNTY',
 'FIPS',
 'ZIP',
 'LAT',
 'LON',
 'HEALTHCARE_EXPENSES',
 'HEALTHCARE_COVERAGE',
 'INCOME',
 'IS_ALIVE']
```

4.5 Data Visualized

To understand the structure of the synthetic patient data, we visualized several key demographic variables. These plots help us evaluate data distribution, detect imbalance, and guide future data cleaning or feature engineering.

- **Gender & Race** distributions highlight population characteristics.

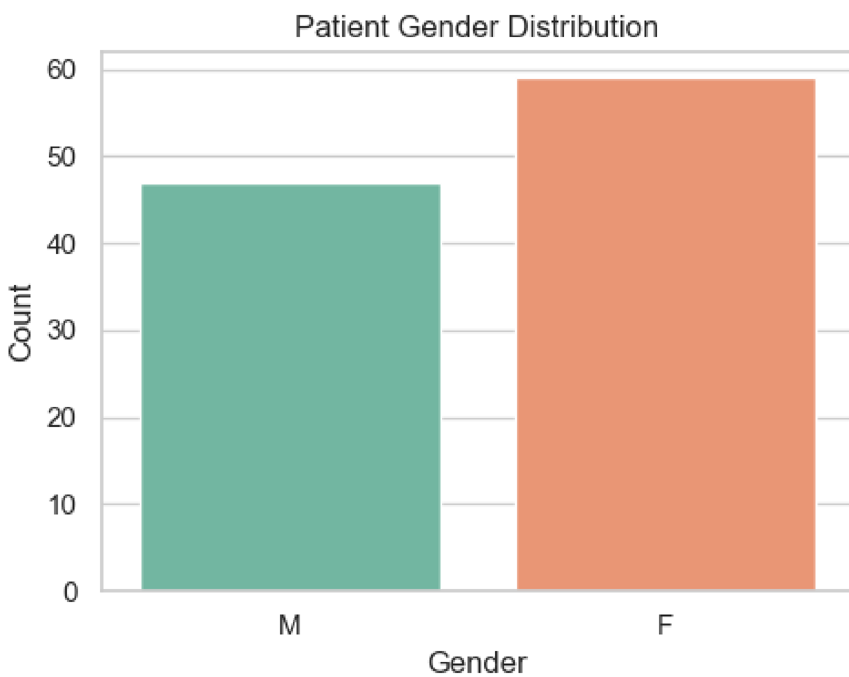
- **Income & Expenses** provide insight into socioeconomic trends, which may affect healthcare behavior or access.

4.5.1 Bar Plot for GENDER

To show gender distribution — good for understanding potential bias or imbalance.

In [264…

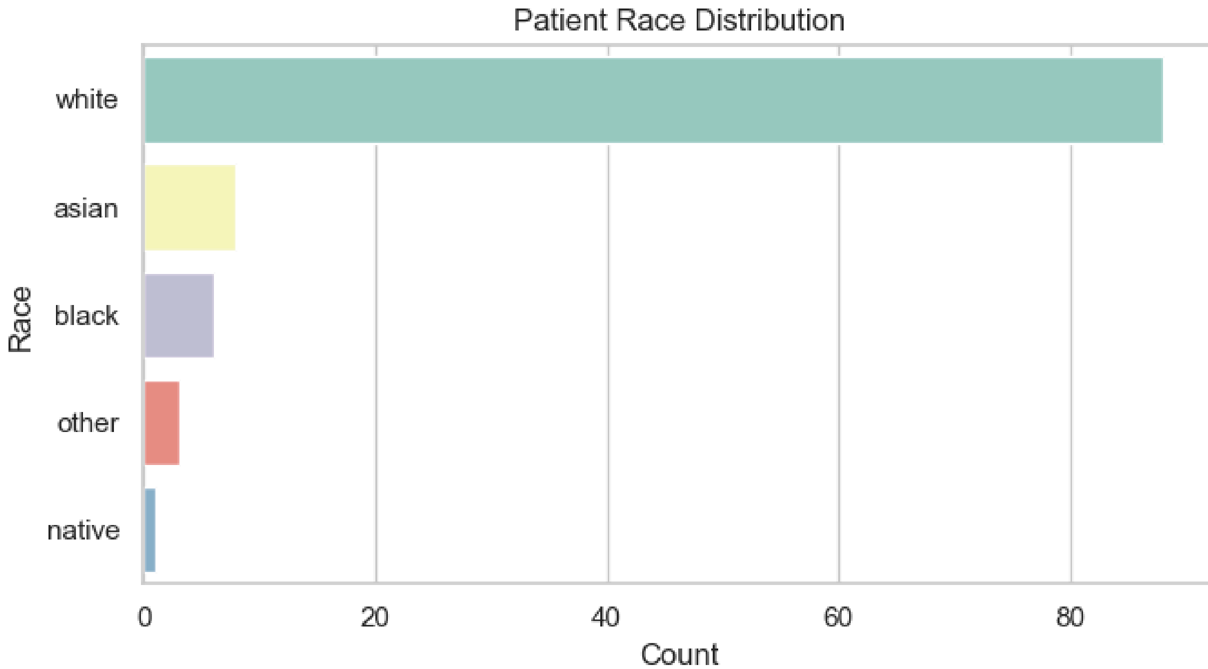
```
plt.figure(figsize=(5, 4))
sns.countplot(x='GENDER', data=synthea_patients_df, palette='Set2')
plt.title('Patient Gender Distribution')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```



4.5.2 Bar Plot for GENDER

In [266…

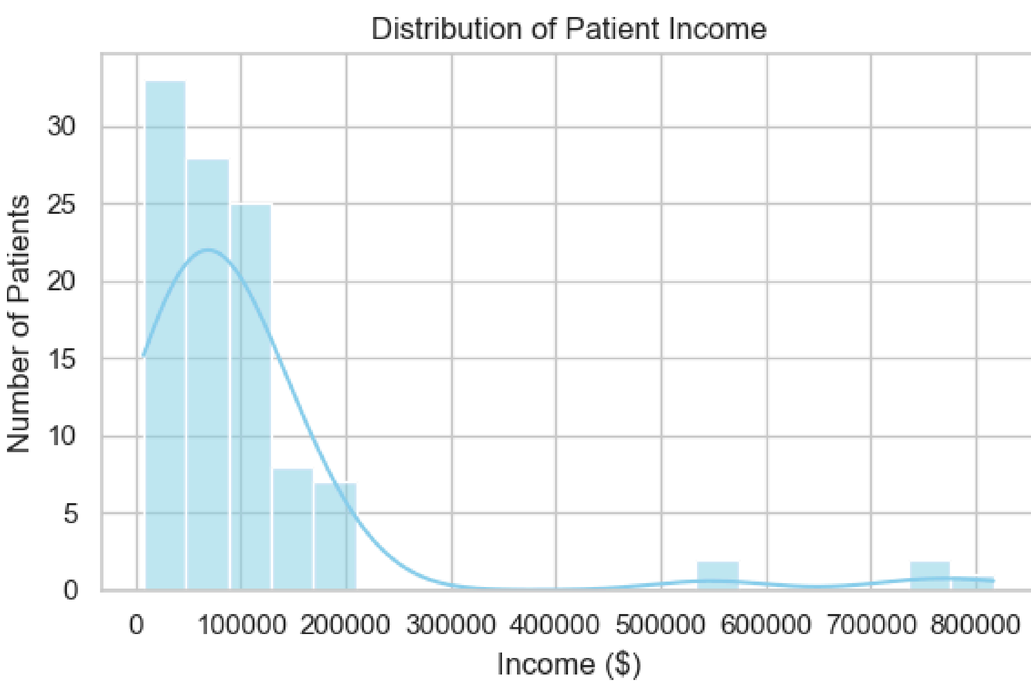
```
plt.figure(figsize=(7, 4))
sns.countplot(y='RACE', data=synthea_patients_df, palette='Set3', order=synthea_patients_df['
plt.title('Patient Race Distribution')
plt.xlabel('Count')
plt.ylabel('Race')
plt.tight_layout()
plt.show()
```



4.5.3 Histogram for INCOME

In [268…

```
plt.figure(figsize=(6, 4))
sns.histplot(synthea_patients_df['INCOME'], bins=20, kde=True, color='skyblue')
plt.title('Distribution of Patient Income')
plt.xlabel('Income ($)')
plt.ylabel('Number of Patients')
plt.tight_layout()
plt.show()
```



IV. Conclusion

In this second progress report, we successfully completed major foundational steps required for developing a robust healthcare fraud detection model. Our work focused on organizing and cleaning three major datasets (CMS, Kaggle, Synthea), performing exploratory data analysis, handling missing values, capping outliers, and visualizing key patterns within each data source.

Key insights include:

- The **CMS dataset** revealed significant variance in average submitted charges, with important patterns by provider geography and service.
- The **Kaggle dataset** displayed a clear class imbalance in the `PotentialFraud` target variable (~9.4% fraud cases), confirming the need for advanced balancing techniques.
- The **Synthea dataset** provided rich synthetic patient-level information, which we cleaned and analyzed for demographic trends such as gender, income, race, and healthcare coverage.

Through descriptive statistics and visualizations, we identified several features that may play a role in predicting fraudulent behavior. We also addressed structural issues in the datasets to ensure compatibility for future modeling.

Looking ahead, our next steps will involve:

- Merging additional data tables (e.g., inpatient, outpatient, claims)
- Conducting feature engineering and transformation
- Training a variety of classification models (logistic regression, decision trees, SVM, boosting, clustering)
- Evaluating performance with metrics appropriate for imbalanced datasets

We remain confident in our timeline and group coordination, and we are well-positioned to complete the modeling, interpretation, and final reporting stages of this project.

GitHub Repository

The full code, data handling process, and visualization scripts are available on GitHub:
🔗 https://github.com/nhanizDee/Predicting-Health-Insurance-Fraud-Using-Machine-Learning

```
In [ ]:
```