Data Science Project - Predicting Fraud in Insurance Claims Using Machine Learning

1. Aims, objectives and plan

1.1 Aims and Objectives of the Project

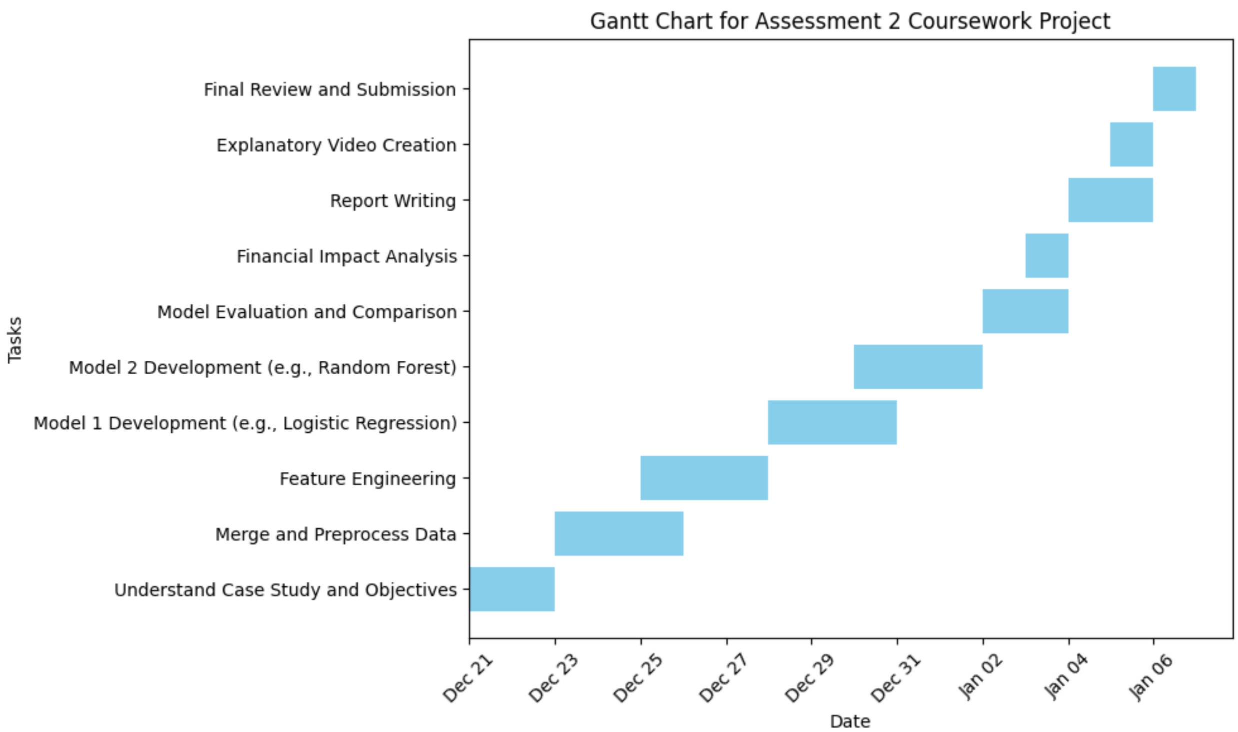
The primary aim of this project is to develop a unbiased predictive model to assist an insurance company in identifying potential fraudulent claims while minimising customer loss due to false referrals. The model should meet the following key business and technical objectives:

1. **Business Perspective**:
    - Using a model in which the gross profit, amounts to double the claims, and their customer base has 10% claim rate, find how many customers they have.
    - Given the model, what the charge for each policy.
    - Quantify the financial impact of prediction errors using a pricing model.
2. **Technical Perspective**:
    - Preprocess the data data removing any noisty attributes, synsoymoys attributes, feature selection/extraction, collinearaity, rescaling, missing and dupicate values and class imbalance
    - Build a robust data analysis pipeline using Python and Jupyter Notebook.
    - Apply two advanced machine learning techniques to solve the binary classification problem.
    - Apply cross validation to the techniques and performance metrics to compare results
    - Test the techniques on the test data and evaluate the performance of the models using appropriate metrics.
    - Ensure balanced performance with an error rate of less than 5%.

```
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
from datetime import datetime, timedelta

# Define tasks, start dates, and durations
tasks = [
    "Understand Case Study and Objectives",
    "Merge and Preprocess Data",
    "Feature Engineering",
    "Model 1 Development (e.g., Logistic Regression)",
    "Model 2 Development (e.g., Random Forest)",
    "Model Evaluation and Comparison",
    "Financial Impact Analysis",
    "Report Writing",
```

```
    "Explanatory Video Creation",
    "Final Review and Submission"
]

start_dates = [
    datetime(2024, 12, 21),
    datetime(2024, 12, 23),
    datetime(2024, 12, 25),
    datetime(2024, 12, 28),
    datetime(2024, 12, 30),
    datetime(2025, 1, 2),
    datetime(2025, 1, 3),
    datetime(2025, 1, 4),
    datetime(2025, 1, 5),
    datetime(2025, 1, 6)
]

durations = [2, 3, 3, 3, 3, 2, 1, 2, 1, 1]  # Durations in days

# Calculate end dates
end_dates = [start_dates[i] + timedelta(days=durations[i]) for i in
range(len(tasks))]

#DataFrame for plotting
gantt_data = pd.DataFrame({
    "Task": tasks,
    "Start": start_dates,
    "End": end_dates
})

# Plotting the Gantt chart
fig, ax = plt.subplots(figsize=(10, 6))

# Iterate through tasks to plot
for i, task in enumerate(gantt_data["Task"]):
    ax.barh(task, (gantt_data["End"][i] - gantt_data["Start"]
[i]).days, left=gantt_data["Start"][i], color="skyblue")

# Format the x-axis for dates
ax.xaxis.set_major_formatter(mdates.DateFormatter("%b %d"))
ax.xaxis.set_major_locator(mdates.DayLocator(interval=2))
plt.xticks(rotation=45)

# labels and title
ax.set_xlabel("Date")
ax.set_ylabel("Tasks")
ax.set_title("Gantt Chart for Assessment 2 Coursework Project")

# Display the chart
```

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



2. Understanding the case study

1.1 Key Points Identified in the Case and Plan to Address Them

1. **Objective of the Model**
- The primary goal is to develop a predictive model that can accurately identify fraudulent insurance claims while minimising financial losses due to false positives and false negatives.
- Plan: Implement a binary classification model that can distinguish between genuine and fraudulent claims with high precision and recall. Evalute two machine learning techniques; a tree based model such as gradientboost and multi-layer perceptron neural network technique. Use balanced performance metrics to evaluate each of the model's effectiveness in minimising errors.
1. **Dataset Quality and Preprocessing**
- The dataset may contain missing values, noisy attributes, redundant information, and class imbalance, which can affect model performance.
- Plan: Perform thorough data preprocessing to handle missing values, remove noisy and redundant attributes, address class imbalance, and rescale numerical features as necessary. Implement feature selection/extraction to reduce dimensionality and collinearity.
1. **Impact of False Positives and False Negatives**

- False positives can lead to genuine claims being flagged as fraudulent, resulting in customer dissatisfaction and financial loss. False negatives allow fraudulent claims to pass undetected, leading to direct financial losses.
- Plan: Implement cost-sensitive learning to incorporate the financial impact of errors into model training. Use balanced performance metrics such as the F1-score, precision, and recall to evaluate models.

1. **Model Validation and Evaluation**

- The model should be validated using cross-validation techniques to ensure robustness and generalisation to unseen data. Performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC should be used to evaluate model effectiveness.
- Plan: Apply k-fold cross-validation to evaluate model performance on training data. Use appropriate performance metrics to compare the effectiveness of the two machine learning techniques. Test the final models on the test data to assess their performance in a real-world scenario.

3. Pre-processing applied

3.1 Merging, Pivoting and melting if necessary

```
import pandas as pd
import numpy as np

claims = pd.read_csv(r'archive 2\archive\TrainData\TrainData\
Train_Claim.csv')
demographics = pd.read_csv(r'archive 2\archive\TrainData\TrainData\
Train_Demographics.csv')
policy = pd.read_csv(r'archive 2\archive\TrainData\TrainData\
Train_Policy.csv')
vehicle = pd.read_csv(r'archive 2\archive\TrainData\TrainData\
Train_Vehicle.csv')
target = pd.read_csv(r'archive 2\archive\TrainData\TrainData\
Traindata_with_Target.csv')
#withouttargets = pd.read_csv(r'archive 2\archive\TrainData\TrainData\
Traindata_withoutTarget.csv')

df_merged = (
    claims
    .merge(demographics, on="CustomerID", how="left")
    .merge(policy, on="CustomerID", how="left")
    .merge(vehicle, on="CustomerID", how="left")
    .merge(target, on="CustomerID", how="left")
)

print(df_merged.shape)
df_merged.head()

(115344, 40)
```

```
  CustomerID DateOfIncident           TypeOfIncident TypeOfCollission
\
0  Cust10000     2015-02-03  Multi-vehicle Collision   Side Collision

1  Cust10000     2015-02-03  Multi-vehicle Collision   Side Collision

2  Cust10000     2015-02-03  Multi-vehicle Collision   Side Collision

3  Cust10000     2015-02-03  Multi-vehicle Collision   Side Collision

4  Cust10001     2015-02-02  Multi-vehicle Collision   Side Collision


  SeverityOfIncident AuthoritiesContacted IncidentState
IncidentCity  \
0         Total Loss               Police        State7        City1

1         Total Loss               Police        State7        City1

2         Total Loss               Police        State7        City1

3         Total Loss               Police        State7        City1

4         Total Loss               Police        State7        City5


  IncidentAddress  IncidentTime  ...  DateOfPolicyCoverage  \
0   Location 1311            17  ...            1998-10-25
1   Location 1311            17  ...            1998-10-25
2   Location 1311            17  ...            1998-10-25
3   Location 1311            17  ...            1998-10-25
4   Location 1311            10  ...            2000-11-15

  InsurancePolicyState  Policy_CombinedSingleLimit
Policy_Deductible  \
0               State1                     100/300              1000

1               State1                     100/300              1000

2               State1                     100/300              1000

3               State1                     100/300              1000

4               State1                     100/300              1000


  PolicyAnnualPremium UmbrellaLimit  InsuredRelationship
VehicleAttribute  \
0              1632.73             0        not-in-family
VehicleID
1              1632.73             0        not-in-family
```

```
VehicleModel
2             1632.73             0        not-in-family
VehicleYOM
3             1632.73             0        not-in-family
VehicleMake
4             1255.19             0        not-in-family
VehicleYOM

   VehicleAttributeDetails  ReportedFraud
0             Vehicle26917              N
1                       A5              N
2                     2008              N
3                     Audi              N
4                     2006              N

[5 rows x 40 columns]
```

```
df_merged.head()  # Verifying column names and keys to merge datasets
and identify potential issues with nomenclature
```

```
  CustomerID DateOfIncident           TypeOfIncident TypeOfCollission
\
0  Cust10000     2015-02-03  Multi-vehicle Collision   Side Collision

1  Cust10000     2015-02-03  Multi-vehicle Collision   Side Collision

2  Cust10000     2015-02-03  Multi-vehicle Collision   Side Collision

3  Cust10000     2015-02-03  Multi-vehicle Collision   Side Collision

4  Cust10001     2015-02-02  Multi-vehicle Collision   Side Collision


  SeverityOfIncident AuthoritiesContacted IncidentState
IncidentCity  \
0         Total Loss               Police        State7        City1

1         Total Loss               Police        State7        City1

2         Total Loss               Police        State7        City1

3         Total Loss               Police        State7        City1

4         Total Loss               Police        State7        City5


  IncidentAddress  IncidentTime  ...  DateOfPolicyCoverage  \
0   Location 1311            17  ...            1998-10-25
1   Location 1311            17  ...            1998-10-25
2   Location 1311            17  ...            1998-10-25
3   Location 1311            17  ...            1998-10-25
```

```
4   Location 1311            10  ...            2000-11-15

  InsurancePolicyState  Policy_CombinedSingleLimit
Policy_Deductible  \
0                State1                     100/300              1000

1                State1                     100/300              1000

2                State1                     100/300              1000

3                State1                     100/300              1000

4                State1                     100/300              1000


  PolicyAnnualPremium UmbrellaLimit  InsuredRelationship
VehicleAttribute  \
0              1632.73             0        not-in-family
VehicleID
1              1632.73             0        not-in-family
VehicleModel
2              1632.73             0        not-in-family
VehicleYOM
3              1632.73             0        not-in-family
VehicleMake
4              1255.19             0        not-in-family
VehicleYOM

   VehicleAttributeDetails  ReportedFraud
0             Vehicle26917              N
1                       A5              N
2                     2008              N
3                     Audi              N
4                     2006              N

[5 rows x 40 columns]

#I will create a key for each instance in the dataset by concatenting
'CustomerID' and 'DateOfIncident' to uniquely identify each claim.
# This will help in pivoting/melting dataset and identifying potential
issues with duplicates

df_merged['CustomerID'] = df_merged['CustomerID'].astype(str)
df_merged['DateOfIncident'] =
pd.to_datetime(df_merged['DateOfIncident'])
df_merged['Unique_ID'] = df_merged['CustomerID'] +
df_merged['DateOfIncident'].dt.strftime('%Y%m%d')
df_merged.head()

  CustomerID DateOfIncident           TypeOfIncident TypeOfCollission
\
```

```
0  Cust10000     2015-02-03  Multi-vehicle Collision   Side Collision

1  Cust10000     2015-02-03  Multi-vehicle Collision   Side Collision

2  Cust10000     2015-02-03  Multi-vehicle Collision   Side Collision

3  Cust10000     2015-02-03  Multi-vehicle Collision   Side Collision

4  Cust10001     2015-02-02  Multi-vehicle Collision   Side Collision


  SeverityOfIncident AuthoritiesContacted IncidentState
IncidentCity  \
0         Total Loss               Police        State7        City1

1         Total Loss               Police        State7        City1

2         Total Loss               Police        State7        City1

3         Total Loss               Police        State7        City1

4         Total Loss               Police        State7        City5


  IncidentAddress  IncidentTime  ...  InsurancePolicyState  \
0   Location 1311            17  ...                State1
1   Location 1311            17  ...                State1
2   Location 1311            17  ...                State1
3   Location 1311            17  ...                State1
4   Location 1311            10  ...                State1

  Policy_CombinedSingleLimit  Policy_Deductible PolicyAnnualPremium  \
0                    100/300               1000             1632.73
1                    100/300               1000             1632.73
2                    100/300               1000             1632.73
3                    100/300               1000             1632.73
4                    100/300               1000             1255.19

  UmbrellaLimit InsuredRelationship  VehicleAttribute  \
0             0       not-in-family         VehicleID
1             0       not-in-family      VehicleModel
2             0       not-in-family        VehicleYOM
3             0       not-in-family       VehicleMake
4             0       not-in-family        VehicleYOM

   VehicleAttributeDetails  ReportedFraud         Unique_ID
0             Vehicle26917              N  Cust1000020150203
1                       A5              N  Cust1000020150203
2                     2008              N  Cust1000020150203
3                     Audi              N  Cust1000020150203
4                     2006              N  Cust1000120150202
```

```
[5 rows x 41 columns]

#create table of distinct values in each column for categorical
columns
distinct_values_cat =
df_merged.select_dtypes(include='object').nunique()
distinct_values_cat

CustomerID                      28836
TypeOfIncident                      4
TypeOfCollission                    4
SeverityOfIncident                  4
AuthoritiesContacted                4
IncidentState                       7
IncidentCity                        7
IncidentAddress                  1000
PropertyDamage                      3
Witnesses                           5
PoliceReport                        3
AmountOfTotalClaim              21976
InsuredGender                       2
InsuredEducationLevel               7
InsuredOccupation                  14
InsuredHobbies                     20
Country                             1
DateOfPolicyCoverage             6779
InsurancePolicyState                3
Policy_CombinedSingleLimit          9
InsuredRelationship                 6
VehicleAttribute                    4
VehicleAttributeDetails         28911
ReportedFraud                       2
Unique_ID                       28836
dtype: int64

#print the first five values of the columns 'VehicleAttribute' and
'VehicleAttributeDetails'

vehicle_attributes = df_merged[['VehicleAttribute',
'VehicleAttributeDetails']]
vehicle_attributes.head()



  VehicleAttribute VehicleAttributeDetails
0        VehicleID            Vehicle26917
1     VehicleModel                      A5
2       VehicleYOM                    2008
3      VehicleMake                    Audi
4       VehicleYOM                    2006
```

The data is "long" rather than "wide." Instead of having one row per vehicle with columns like VehicleID, VehicleModel, VehicleYOM, VehicleMake, we see multiple rows for a single vehicle record, each row describing one attribute. I'll pivot the data to make it "wide" so that each vehicle record is represented by a single row with all attributes as columns.

```
#I will write key processes as methods to be reused in the pipeline if
needed

def group_vehicle_attributes_by_customer_and_date(df):
    """
    Groups rows by (CustomerID, DateOfIncident) and includes:
      - Aggregated leftover columns (e.g., TypeOfIncident,
SeverityOfIncident, etc.)
      - Pivoted VehicleAttribute columns (VehicleID, VehicleModel,
VehicleYOM, VehicleMake, etc.)

    Returns a single DataFrame with all columns plus pivoted vehicle
attributes.
    """

    #Identify columns that belong to VehicleAttribute pivoting
    #  and the columns we want to aggregate by (CustomerID,
DateOfIncident, etc.).
    pivot_cols = ["VehicleAttribute", "VehicleAttributeDetails"]
    group_cols = ["CustomerID", "DateOfIncident"]

    # The leftover columns are the ones we want to keep as-is.

    leftover_cols = [
        c for c in df.columns
        if c not in (group_cols + pivot_cols)
    ]

    # Aggregate leftover columns by taking the first row in each
(CustomerID, DateOfIncident) group

    df_agg = (
        df.groupby(group_cols, as_index=False)[leftover_cols]
          .agg("first")
    )

    # Pivot the vehicle attributes so each attribute becomes a column

    pivoted = (
        df.pivot_table(
            index=group_cols,
            columns="VehicleAttribute",
            values="VehicleAttributeDetails",
            aggfunc=lambda x: ",".join(x)  # combine multiple values
with commas
```

```
        )
        .reset_index()
    )

   #flatten pivot table if needed
    pivoted.columns.name = None  # remove top-level name
    pivoted = pivoted.rename_axis(None, axis=1)  # remove index name
if needed

    # Merge the aggregated leftover columns with the pivoted vehicle
attributes
    final_df = pd.merge(df_agg, pivoted, on=group_cols, how="left")

    # Reorder columns so that group_cols come first, then
leftover_cols, then pivoted columns
    pivoted_attribs = sorted(set(pivoted.columns) - set(group_cols))
    final_cols = group_cols + leftover_cols + pivoted_attribs
    final_cols = [c for c in final_cols if c in final_df.columns]  #
only keep existing
    final_df = final_df[final_cols]

    return final_df

df_pivot = group_vehicle_attributes_by_customer_and_date(df_merged)
df_pivot
```

```
      CustomerID DateOfIncident            TypeOfIncident
TypeOfCollission  \
0      Cust10000     2015-02-03   Multi-vehicle Collision   Side
Collision
1      Cust10001     2015-02-02   Multi-vehicle Collision   Side
Collision
2      Cust10002     2015-01-15  Single Vehicle Collision   Side
Collision
3      Cust10003     2015-01-19  Single Vehicle Collision   Side
Collision
4      Cust10004     2015-01-09  Single Vehicle Collision   Rear
Collision
...          ...            ...                       ...
...
28831   Cust9993     2015-01-24             Vehicle Theft
?
28832   Cust9994     2015-02-09  Single Vehicle Collision  Front
Collision
28833   Cust9996     2015-01-28  Single Vehicle Collision   Rear
Collision
28834   Cust9997     2015-01-28  Single Vehicle Collision   Rear
Collision
28835   Cust9999     2015-01-13  Single Vehicle Collision  Front
Collision
```

```
      SeverityOfIncident AuthoritiesContacted IncidentState
IncidentCity  \
0            Total Loss               Police        State7
City1
1            Total Loss               Police        State7
City5
2          Minor Damage                Other        State8
City6
3          Minor Damage                Other        State9
City6
4          Minor Damage                 Fire        State8
City6
...                 ...                  ...           ...           .
..
28831     Trivial Damage               Police        State9
City4
28832       Minor Damage                 Fire        State8
City3
28833       Minor Damage                 Fire        State9
City7
28834       Minor Damage            Ambulance        State9
City3
28835         Total Loss                Other        State8
City3

      IncidentAddress  IncidentTime  ...  Policy_Deductible  \
0       Location 1311            17  ...               1000
1       Location 1311            10  ...               1000
2       Location 2081            22  ...                617
3       Location 2081            22  ...                722
4       Location 1695            10  ...                500
...               ...           ...  ...                ...
28831   Location 1890             3  ...                655
28832   Location 2097            17  ...               1089
28833   Location 1452             1  ...                787
28834   Location 1876             1  ...                780
28835   Location 1874             9  ...               2000

      PolicyAnnualPremium  UmbrellaLimit InsuredRelationship
ReportedFraud  \
0                 1632.73              0       not-in-family
N
1                 1255.19              0       not-in-family
N
2                 1373.38              0                wife
N
3                 1337.60              0          own-child
N
4                 1353.73        4279863           unmarried
```

```
N
...                    ...            ...                   ...
...
28831              1276.01              0           unmarried
N
28832              1273.38              0           unmarried
N
28833              1380.92        3448735           own-child
N
28834              1389.29        3364301       not-in-family
N
28835               928.43        2909175             husband
N

               Unique_ID     VehicleID  VehicleMake  VehicleModel
VehicleYOM
0      Cust1000020150203  Vehicle26917         Audi            A5
2008
1      Cust1000120150202  Vehicle15893         Audi            A5
2006
2      Cust1000220150115   Vehicle5152   Volkswagen         Jetta
1999
3      Cust1000320150119  Vehicle37363   Volkswagen         Jetta
2003
4      Cust1000420150109  Vehicle28633       Toyota           CRV
2010
...                  ...           ...          ...           ...
...
28831   Cust999320150124  Vehicle13568       Suburu       Impreza
2007
28832   Cust999420150209  Vehicle19810         Jeep      Wrangler
2003
28833   Cust999620150128   Vehicle3339       Suburu        Legacy
2004
28834   Cust999720150128  Vehicle10240       Suburu     Forrestor
2004
28835   Cust999920150113  Vehicle39163       Suburu          E400
2007

[28836 rows x 43 columns]
```

3.2 Identifying and dealing with class imbalance, if necessary

Data Splitting and Validation

To avoid data leakage, I will split the data into training and test sets before performing any preprocessing steps. I will use a stratified split to ensure that the class distribution is maintained in both sets. I will also perform a preliminary check to ensure that the split was successful and that the class distribution is balanced in both sets.

```python
# split the data

df = df_pivot
X = df.drop(columns=["ReportedFraud"])
y = df["ReportedFraud"]

from sklearn.model_selection import train_test_split

# Train (80%) vs. Test (20%)
X_train, X_test, y_train, y_test = train_test_split(
    X,
    y,
    test_size=0.20,         # 20% for test
    random_state=42,        # ensures reproducibility
    stratify=y              # maintain class ratio, e.g., fraud/non-
fraud
)

print(X_train.shape)
print(y_train.shape)

print(X_test.shape)
print(y_test.shape)
```

```
(23068, 42)
(23068,)
(5768, 42)
(5768,)
```

```python
# percentage of each class in y_train
fraud_train_counts = y_train.value_counts()
fraud_train_percent = y_train.value_counts(normalize=True) * 100


print("Fraud Distribution in the Training Set:")
for fraud_class in fraud_train_counts.index:
    count = fraud_train_counts[fraud_class]
    percent = fraud_train_percent[fraud_class]
    print(f"  {fraud_class}: {count} instances ({percent:.2f}%)")
```

```
Fraud Distribution in the Training Set:
  N: 16840 instances (73.00%)
  Y: 6228 instances (27.00%)
```

```python
# Percentage of each class in y_test
fraud_test_counts = y_test.value_counts()
fraud_test_percent = y_test.value_counts(normalize=True) * 100


print("Fraud Distribution in the Test:")
for fraud_class in fraud_test_counts.index:
```

```
    count = fraud_test_counts[fraud_class]
    percent = fraud_test_percent[fraud_class]
    print(f"  {fraud_class}: {count} instances ({percent:.2f}%)")

Fraud Distribution in the Test:
  N: 4211 instances (73.01%)
  Y: 1557 instances (26.99%)
```

The split suggests that the class distribution is maintained in both the training and test sets, indicating a successful stratified split. The training set contains 80% of the data, while the test set contains 20%. The class distribution is balanced in both sets, with approximately 27% of claims being fraudulent in each set.

3.3 Appropriate feature extraction, if necessary

Dates and Times

The dates and times can be extracted from the 'DateOfIncident' and 'DateOfClaim' columns to create new features such as 'DayOfWeek', 'Month', 'Year', 'Weekday', 'Weekend', 'TimeOfDay', etc. These features can make it more convient for machine learning models to learn patterns in the data aswell as for calculations.

```
def process_incident_and_policy_dates(df,
                                      incident_col='DateOfIncident',

policy_col='DateOfPolicyCoverage',
incident_year_col='IncidentYear',vehicle_yom_col='VehicleYOM'):
    """
    Converts the incident and policy coverage dates to datetime,
    then creates columns for year/month/day of incident and
    calculates policy age in days.

    Parameters:

    df : pd.DataFrame
        The DataFrame containing date columns.
    incident_col : str
        Column name with the incident date.
    policy_col : str
        Column name with the policy coverage start date.

    Returns:

    pd.DataFrame
        The original DataFrame with new columns added:
            - IncidentYear
            - IncidentMonth
            - IncidentDay
```

```
            - PolicyAgeDays
    """

    # Convert incident date to datetime
    df[incident_col] = pd.to_datetime(df[incident_col],
errors='coerce')

    # Extract components of the incident date
    df['IncidentYear'] = df[incident_col].dt.year
    df['IncidentMonth'] = df[incident_col].dt.month
    df['IncidentDay'] = df[incident_col].dt.day

    # Convert policy coverage date to datetime
    df[policy_col] = pd.to_datetime(df[policy_col], errors='coerce')

    # Calculate the number of days between incident and policy
coverage
    df['PolicyAgeDays'] = (df[incident_col] - df[policy_col]).dt.days

    # Convert both columns to numeric (int)
    df[incident_year_col] = pd.to_numeric(df[incident_year_col],
errors='coerce')
    df[vehicle_yom_col]   = pd.to_numeric(df[vehicle_yom_col],
errors='coerce')

    # Calculate age at incident in years
    df['AgeAtIncident'] = df[incident_year_col] - df[vehicle_yom_col]

    return df

#apply the function to the training and test data
X_train_grouped = process_incident_and_policy_dates(X_train)
X_test_grouped = process_incident_and_policy_dates(X_test)

#check for data integrity
print(X_train_grouped['Unique_ID'].nunique)
print(X_train_grouped.shape)
print(X_test_grouped.shape)
print(y_train.shape)
print(y_test.shape)
```

```
<bound method IndexOpsMixin.nunique of 20936    Cust3542720150227
19307    Cust3344820150208
2609     Cust1315920150117
15420    Cust2870520150225
21007    Cust3551220150110
               ...
27962     Cust881320150222
10263    Cust2239220150225
11822    Cust2422820150114
```

```
8667     Cust2048020150216
10825    Cust2303720150103
Name: Unique_ID, Length: 23068, dtype: object>
(23068, 47)
(5768, 47)
(23068,)
(5768,)
```

3.4 Dealing with Missing Values (Imputation/Filtering) without Leakage

```
#missing values in the training set
missing_values = X_train_grouped.isnull().sum()
missing_values = missing_values[missing_values > 0]
missing_values

AuthoritiesContacted    2144
InsuredGender             23
Country                    1
dtype: int64

#other categories of missing values such as 'Unknown' or 'MISSEDDATA'
or '?'
unknown_values = X_train_grouped.isin(['Unknown', 'MISSEDDATA',
'?']).sum()
unknown_values = unknown_values[unknown_values > 0]
unknown_values

TypeOfCollission      4104
PropertyDamage        8375
PoliceReport          7830
AmountOfTotalClaim      40
dtype: int64

#other potential missing data categories such as 'Not Available' or
'N/A'
na_values = X_train_grouped.isin(['Not Available', 'N/A']).sum()
na_values = na_values[na_values > 0]
na_values

Series([], dtype: int64)
```

Unifying Missing Values

```

def unify_missing_values(df, extra_missing=None):
    """
    Converts placeholders like '?' and 'MISSEDDATA' (and any extra you
pass) into np.nan.
    Returns a new DataFrame with unified missing values.
```

```
    Parameters:

    df : pd.DataFrame
        The DataFrame whose missing placeholders you want to
standardize.
    extra_missing : list of str, optional
        Additional string placeholders that should be converted to
np.nan.

    Returns:

    pd.DataFrame
        A copy of the original DataFrame, with all missing
placeholders replaced by np.nan.
    """
    # Default placeholders
    placeholders = ['?', 'MISSEDDATA']

    #  passed additional placeholders
    if extra_missing is not None:
        placeholders.extend(extra_missing)

    # Replace all placeholders with np.nan

    df_clean = df.replace(placeholders, np.nan)

    return df_clean

#apply the function to the training and test data
X_train_clean = unify_missing_values(X_train_grouped)
X_test_clean = unify_missing_values(X_test_grouped)

print(X_train_clean.shape)
print(X_test_clean.shape)
```

```
(23068, 47)
(5768, 47)
```

Check for Missing Values

```
def check_missing_values(df):
    """
    Checks for missing values in a DataFrame and returns a summary
DataFrame
    containing both the absolute number of missing values and their
percentage.
```

```
    Parameters

    df : pd.DataFrame
        The DataFrame to analyse.

    Returns

    pd.DataFrame
        A DataFrame with two columns:
        - "Missing Values" (the count of NaNs in each column)
        - "Percentage Missing (%)" (the percentage of NaNs in that
column).
        Only columns with missing values are listed.

    """
    # Count total NaNs in each column
    missing = df.isnull().sum()
    # Filter out columns that have no missing values
    missing = missing[missing > 0]
    # Calculate the percentage of missing values
    percentage_missing = (missing / len(df)) * 100

    # Create a summary DataFrame
    missing_values_df = pd.DataFrame({
        "Missing Values": missing,
        "Percentage Missing (%)": percentage_missing
    })

    return missing_values_df

missing_values_train_train = check_missing_values(X_train_clean)
missing_values_train_train
```

	Missing Values	Percentage Missing (%)
TypeOfCollission	4104	17.790879
AuthoritiesContacted	2144	9.294260
PropertyDamage	8375	36.305705
PoliceReport	7830	33.943125
AmountOfTotalClaim	40	0.173400
InsuredGender	23	0.099705
Country	1	0.004335

```
missing_values_test = check_missing_values(X_test_clean)
missing_values_test
```

	Missing Values	Percentage Missing (%)
TypeOfCollission	1058	18.342580
AuthoritiesContacted	548	9.500693
PropertyDamage	2084	36.130374
PoliceReport	1975	34.240638

```
AmountOfTotalClaim                   10                 0.173370
InsuredGender                         7                 0.121359
Country                               1                 0.017337
```

Imputation Strategy

In order to develop an imputation strategy, I will see if gender has any direct bearing on fields such as hobbies and interests. If there is a correlation, the gender can be inferred from the hobbies and interests.

```
# Group by Hobbies and Gender, count number of rows
hobby_gender_counts = (
    X_train_clean
    .groupby(['InsuredHobbies', 'InsuredGender'])
    .size()
    .unstack(fill_value=0)  # Convert to columns = ['F', 'M'], fill
missing with 0
)

# Convert counts to percentages (row-wise)
hobby_gender_percent =
hobby_gender_counts.div(hobby_gender_counts.sum(axis=1), axis=0) * 100

# Print or inspect
print(hobby_gender_percent)
```

```
InsuredGender      FEMALE       MALE
InsuredHobbies
base-jumping    47.147651  52.852349
basketball      46.650426  53.349574
board-games     53.019538  46.980462
bungie-jumping  54.829545  45.170455
camping         52.193309  47.806691
chess           57.113188  42.886812
cross-fit       51.717370  48.282630
dancing         59.756098  40.243902
exercise        61.624204  38.375796
golf            54.402790  45.597210
hiking          51.219512  48.780488
kayaking        65.495706  34.504294
movies          51.915240  48.084760
paintball       57.528090  42.471910
polo            48.805147  51.194853
reading         54.838710  45.161290
skydiving       57.592093  42.407907
sleeping        55.730810  44.269190
video-games     55.460017  44.539983
yachting        46.740995  53.259005
```

```python
# Group by Occupation and Gender, get counts
occ_gender_counts = (
    X_train_clean
    .groupby(['InsuredOccupation', 'InsuredGender'])
    .size()
    .unstack(fill_value=0)
)

# Convert to percentages
occ_gender_percent =
occ_gender_counts.div(occ_gender_counts.sum(axis=1), axis=0) * 100

# Print or inspect
print(occ_gender_percent)
```

```
InsuredGender          FEMALE       MALE
InsuredOccupation
adm-clerical        58.942559  41.057441
armed-forces        50.945699  49.054301
craft-repair        54.821742  45.178258
exec-managerial     48.711944  51.288056
farming-fishing     58.550039  41.449961
handlers-cleaners   52.468619  47.531381
machine-op-inspct   51.351351  48.648649
other-service       52.918538  47.081462
priv-house-serv     51.875000  48.125000
prof-specialty      56.825397  43.174603
protective-serv     56.350365  43.649635
sales               57.017544  42.982456
tech-support        58.810198  41.189802
transport-moving    52.797619  47.202381
```

No evident correlation for gender with hobbies and interests. Therefore, I will use the mode imputation strategy to fill missing values

Observations:

Categorical and numerical features with low or medium percentage missing values can be need not be dropped and can be imputed with a separate category called 'Unknown' or the mode value.

Categorical Values: AmountOfTotalClaim, InsuredGender, Country have very low missing rates (<1%) TypeOfCollission has moderate missing (~18%) AuthoritiesContacted has moderate missing (~9%)

Numerical Amount of Total Claim has very low missing rates (<1%) and can be imputed with the median value.

Categories with high missing values: PropertyDamage and PoliceReport each have over 30% missing. I can evaluate if losing an feature is worse than risking biased imputations. In prediction fraud, these features may be important, so we will impute them with a separate category called 'Unknown', as the missing values may carry information and are not above 40%

```
#change AmountOfTotalClaim to float
df = X_train_clean
df['AmountOfTotalClaim'] = df['AmountOfTotalClaim'].astype(float)

df = X_test_clean
df['AmountOfTotalClaim'] = df['AmountOfTotalClaim'].astype(float)
```

3.5 Dealing with duplicate values, if necessary

```
# Based on unique ID, there are no duplicate rows in the dataset.
```

3.6 Categorical and Numerical Encoding if Necessary

I will identify categorical and numerical columns in the dataset and encode them appropriately. Categorical columns will be one-hot encoded, while numerical columns can be scaled if needed. I will also check for any remaining missing values and handle them accordingly. I can also use frequency encoding for categorical columns with high cardinality to reduce dimensionality.

```
def get_numeric_and_categorical_columns(df):
    """
    Identifies numeric  and categorical  columns in the DataFrame.

    Parameters

    df : pd.DataFrame
        The DataFrame to analyze.

    Returns

    numerical_columns : list
        A list of column names that have int or float data types.
    categorical_columns : list
        A list of column names that have object data types.

    """
    numerical_columns = df.select_dtypes(include=[int,
float]).columns.tolist()
    categorical_columns =
df.select_dtypes(include=['object']).columns.tolist()

    return numerical_columns, categorical_columns


num_cols, cat_cols =
get_numeric_and_categorical_columns(X_train_clean)
print("Numeric columns:", num_cols)
print("Categorical columns:", cat_cols)
```

```
Numeric columns: ['IncidentTime', 'NumberOfVehicles',
'BodilyInjuries', 'AmountOfTotalClaim', 'AmountOfInjuryClaim',
'AmountOfPropertyClaim', 'AmountOfVehicleDamage', 'InsuredAge',
'InsuredZipCode', 'CapitalGains', 'CapitalLoss',
'InsurancePolicyNumber', 'CustomerLoyaltyPeriod', 'Policy_Deductible',
'PolicyAnnualPremium', 'UmbrellaLimit', 'VehicleYOM', 'IncidentYear',
'IncidentMonth', 'IncidentDay', 'PolicyAgeDays', 'AgeAtIncident']
Categorical columns: ['CustomerID', 'TypeOfIncident',
'TypeOfCollission', 'SeverityOfIncident', 'AuthoritiesContacted',
'IncidentState', 'IncidentCity', 'IncidentAddress', 'PropertyDamage',
'Witnesses', 'PoliceReport', 'InsuredGender', 'InsuredEducationLevel',
'InsuredOccupation', 'InsuredHobbies', 'Country',
'InsurancePolicyState', 'Policy_CombinedSingleLimit',
'InsuredRelationship', 'Unique_ID', 'VehicleID', 'VehicleMake',
'VehicleModel']
```

```
from sklearn.impute import SimpleImputer

numeric_imputer = SimpleImputer(strategy='mean')

categorical_imputer = SimpleImputer(strategy='most_frequent')

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

# Define separate pipelines for numeric and categorical
numeric_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='mean'))
    # Add other numeric transforms if needed, e.g. StandardScaler
])

categorical_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='most_frequent'))
    # Add other categorical transforms if needed, e.g. OneHotEncoder
])

# Combine them in a ColumnTransformer
preprocessor = ColumnTransformer([
    ('num', numeric_pipeline, num_cols),
    ('cat', categorical_pipeline, cat_cols)
])



# Fit on training data
preprocessor.fit(X_train_clean)

# Transform training data
X_train_imputed = preprocessor.transform(X_train_clean)

# Transform test data
```

```
X_test_imputed = preprocessor.transform(X_test_clean)

#make dataframe
X_train_imputed = pd.DataFrame(X_train_imputed, columns=num_cols +
cat_cols)
X_test_imputed = pd.DataFrame(X_test_imputed, columns=num_cols +
cat_cols)

check_missing_values(X_train_imputed)
```

```
                      Missing Values  Percentage Missing (%)
AuthoritiesContacted            2144                9.294260
InsuredGender                     23                0.099705
Country                            1                0.004335
```

```
#add 'missing' category to categorical columns with missing values
X_train_imputed.fillna('missing', inplace=True)
X_test_imputed.fillna('missing', inplace=True)
```

```
C:\Users\saqib\AppData\Local\Temp\ipykernel_30288\1039554909.py:2:
FutureWarning: Downcasting object dtype arrays
on .fillna, .ffill, .bfill is deprecated and will change in a future
version. Call result.infer_objects(copy=False) instead. To opt-in to
the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  X_train_imputed.fillna('missing', inplace=True)
C:\Users\saqib\AppData\Local\Temp\ipykernel_30288\1039554909.py:3:
FutureWarning: Downcasting object dtype arrays
on .fillna, .ffill, .bfill is deprecated and will change in a future
version. Call result.infer_objects(copy=False) instead. To opt-in to
the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  X_test_imputed.fillna('missing', inplace=True)
```

```
#check missing values
print("Missing values in the training set after adding 'missing'
category:")
check_missing_values(X_train_imputed)
check_missing_values(X_test_imputed)
```

```
Missing values in the training set after adding 'missing' category:

Empty DataFrame
Columns: [Missing Values, Percentage Missing (%)]
Index: []
```

Frequency Encoding

```
#distinct object columns
```

```
distinct_values =
X_train_clean.select_dtypes(include='object').nunique()
#distinct_values = X_train_clean.nunique()
distinct_values
```

```
CustomerID                      23068
TypeOfIncident                      4
TypeOfCollission                    3
SeverityOfIncident                  4
AuthoritiesContacted                4
IncidentState                       7
IncidentCity                        7
IncidentAddress                  1000
PropertyDamage                      2
Witnesses                           5
PoliceReport                        2
InsuredGender                       2
InsuredEducationLevel               7
InsuredOccupation                  14
InsuredHobbies                     20
Country                             1
InsurancePolicyState                3
Policy_CombinedSingleLimit          9
InsuredRelationship                 6
Unique_ID                       23068
VehicleID                       23068
VehicleMake                        15
VehicleModel                       39
dtype: int64
```

```
def frequency_encode_columns(df, columns, drop_original=False,
suffix="_freq"):
    """
    Applies frequency encoding to the given columns in a DataFrame.
    Creates new columns named <col> + <suffix> by default.

    Parameters

    df : pd.DataFrame
        The DataFrame with columns to be encoded.
    columns : list of str
        A list of column names in df to frequency-encode.
    drop_original : bool, optional
        If True, drop the original columns after encoding. Default is
False.
    suffix : str, optional
        Suffix to append to the new encoded column names. Default is
"_freq".
```

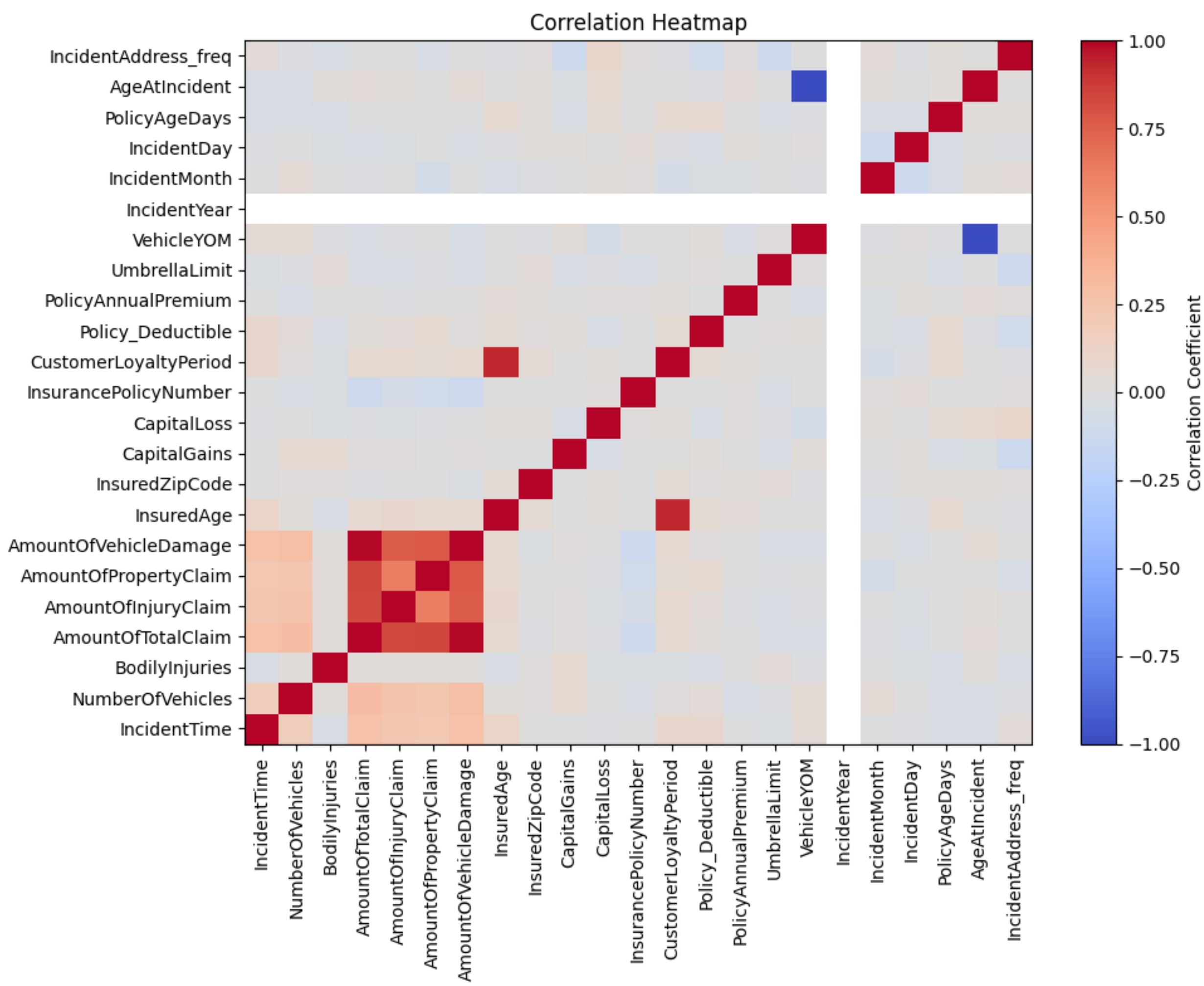
```
    Returns

    pd.DataFrame
        A DataFrame with the new frequency-encoded columns added.
        If drop_original=True, the original columns are removed.
    """

    df_encoded = df.copy()  # Work on a copy

    for col in columns:
        # 1) Compute frequency counts
        freq_map = df_encoded[col].value_counts().to_dict()

        # 2) Create the frequency-encoded column
        new_col_name = col + suffix
        df_encoded[new_col_name] = df_encoded[col].map(freq_map)

        # 3) Optionally drop the original column
        if drop_original:
            df_encoded.drop(columns=[col], inplace=True)

    return df_encoded

#apply frequency encoding to the 'IncidentAddress' column
X_train_fre_encoded = frequency_encode_columns(X_train_clean,
["IncidentAddress"], drop_original=True)
X_test_fre_encoded = frequency_encode_columns(X_test_clean,
["IncidentAddress"], drop_original=True)
```

3.7 Dealing with correlation and collinearity, if necessary

Correlation and collinearity will be assessed to identify redundant features that may affect model performance.

```
import matplotlib.pyplot as plt
import numpy as np


corr_matrix = X_train_fre_encoded.corr(numeric_only=True)

plt.figure(figsize=(10, 8))

# Plot the correlation matrix
im = plt.imshow(corr_matrix, cmap="coolwarm", origin="lower",
aspect="auto")

# Add a colorbar
cbar = plt.colorbar(im)
```

```
cbar.set_label("Correlation Coefficient")

# Add title
plt.title("Correlation Heatmap")

# Set ticks and labels for x and y axes
num_features = len(corr_matrix.columns)
plt.xticks(np.arange(num_features), corr_matrix.columns, rotation=90)
plt.yticks(np.arange(num_features), corr_matrix.columns)


plt.tight_layout()

plt.show()
```



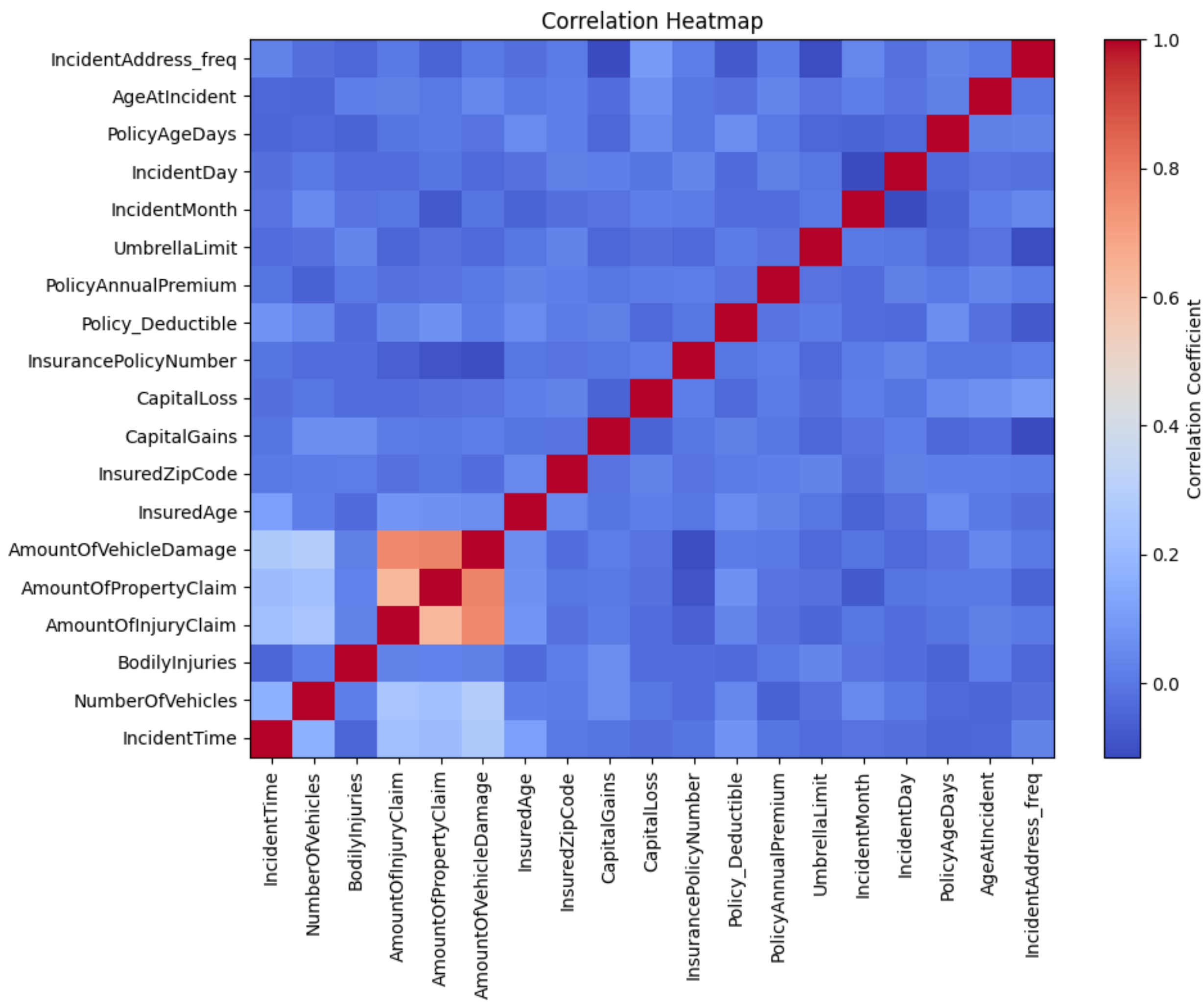

```
# Select numeric columns for correlation matrix calculation
numeric_data = X_train_fre_encoded.select_dtypes(include=[np.number])
```

```
# Calculate correlation matrix of numeric features
corr_matrix = numeric_data.corr().abs()

# Upper triangle of the correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape),
k=1).astype(bool))

# Identify columns with correlation above a chosen threshold
threshold = 0.9
redundant_features = [
    column for column in upper.columns if any(upper[column] >
threshold)
]

print("Highly correlated features:", redundant_features)
```

```
Highly correlated features: ['AmountOfVehicleDamage',
'CustomerLoyaltyPeriod', 'AgeAtIncident']
```

```
#following columns can be removed as they have little to no impact on
the target e.g. VehicleID,
#or are redundant e.g. Unique_ID
# or are highly correlated and represent the same information e.g.
Customer loyalty period and age at incident

#Incident Year has a variance of 0, so it can be removed as well

columns_to_remove =
['IncidentYear','CustomerID','DateOfPolicyCoverage','VehicleID','Count
ry','VehicleYOM','CustomerLoyaltyPeriod','Unique_ID','AmountOfTotalCla
im']

#remove columns_to_remove from training and test sets

X_train_fre_encoded =
X_train_fre_encoded.drop(columns=columns_to_remove)
X_test_fre_encoded =
X_test_fre_encoded.drop(columns=columns_to_remove)

import matplotlib.pyplot as plt
import numpy as np

# Compute correlation matrix
corr_matrix = X_train_fre_encoded.corr(numeric_only=True)

plt.figure(figsize=(10, 8))

# Display the correlation matrix using imshow
im = plt.imshow(
    corr_matrix,
```

```
    cmap="coolwarm",    # same color scheme as in Seaborn
    aspect="auto",      # adjusts aspect ratio
    origin="lower"      # so that the [0,0] index is at the bottom-left
)

# Add a colorbar to show correlation scale
cbar = plt.colorbar(im)
cbar.set_label("Correlation Coefficient")

# Label the axes with feature names
num_features = len(corr_matrix.columns)
plt.xticks(np.arange(num_features), corr_matrix.columns, rotation=90)
plt.yticks(np.arange(num_features), corr_matrix.columns)

plt.title("Correlation Heatmap")
plt.tight_layout()   # avoids label cut-off
plt.show()
```



3.8 Other Pre-processing

Certain fields have a high level of distinct values, and are not suitable for one-hot encoding and can lead to the curse of dimensionality. I will evaluate the cardinality of these fields and decide on an appropriate encoding strategy.

Feature Engineering: Zip Code Encoding

```
df = X_train_fre_encoded

unique_zip_codes = df['InsuredZipCode'].unique().size

print(f"Unique zip codes: {unique_zip_codes}")
```

```
Unique zip codes: 995
```

It seems there are 995 unique values for the insured zip code, which is too many for one-hot encoding. This can be droped or grouped into regions. As region can play an important part in fraud detection, it will be grouped into regions. The codes themselves do correlate with the Indian postal codes as the 4 and 6 digit at the start match the Indian postal code system. There are no codes started with any other digit. The codes will be grouped into regions based on the first two digits of the postal code. I will use Indian region names as labels for the grouping knowing that the codes are there simply for purposes of prediction and not for actual location.

Every code in the list falls into either Maharashtra (40–44), Madhya Pradesh (45–48), or Tamil Nadu (60–66).

```
def pin_to_region(pin_code):
    # Convert to string just in case
    s = str(pin_code)
    first_two = int(s[:2])

    if 40 <= first_two <= 44:
        return "Maharashtra"
    elif 45 <= first_two <= 48:
        return "Madhya Pradesh"
    elif 60 <= first_two <= 66:
        return "Tamil Nadu"
    else:
        return "Other"  # or handle other states as needed

#Apply to training set

X_train_fre_encoded['Region'] =
X_train_fre_encoded['InsuredZipCode'].apply(pin_to_region)
X_train_fre_encoded =
X_train_fre_encoded.drop(columns=['InsuredZipCode'])
X_train_fre_encoded['Region'].value_counts()
```

```
Region
Madhya Pradesh    9902
Tamil Nadu        6978
Maharashtra       6188
Name: count, dtype: int64
```

```
#Apply to test set

X_test_fre_encoded['Region'] =
X_test_fre_encoded['InsuredZipCode'].apply(pin_to_region)
X_test_fre_encoded =
X_test_fre_encoded.drop(columns=['InsuredZipCode'])
X_test_fre_encoded['Region'].value_counts()
```

```
Region
Madhya Pradesh    2505
Tamil Nadu        1732
Maharashtra       1531
Name: count, dtype: int64
```

3.9 Variance analysis, if necessary

```
variance_per_column = X_train_fre_encoded.var(numeric_only=True)  # or
df.std()

variance_per_column
```

```
IncidentTime                3.791831e+01
NumberOfVehicles            9.637541e-01
BodilyInjuries              6.131465e-01
AmountOfInjuryClaim         1.943763e+07
AmountOfPropertyClaim       1.899265e+07
AmountOfVehicleDamage       3.217226e+08
InsuredAge                  6.418861e+01
CapitalGains                7.636088e+08
CapitalLoss                 7.770723e+08
InsurancePolicyNumber       1.233447e+08
Policy_Deductible           2.981809e+05
PolicyAnnualPremium         4.998944e+04
UmbrellaLimit               3.904602e+12
IncidentMonth               2.660365e-01
IncidentDay                 5.781666e+01
PolicyAgeDays               5.717444e+06
AgeAtIncident               2.822925e+01
IncidentAddress_freq        1.049851e+02
dtype: float64
```

- IncidentYear has 0 variance and can be dropped as it does not provide any information to the model.
- InsurancePolicyNumber can also be dropped as it provides no information to the model.
- Small variance columns such as BodilyInjuries and Number of Vehicles Involved will be kept as they may still provide valuable information for the model.

```
#drop InsurancePolicyNumber and IncidentYear

X_train_filled = 
X_train_fre_encoded.drop(columns=['InsurancePolicyNumber','DateOfIncid
ent'])
X_test_filled = 
X_test_fre_encoded.drop(columns=['InsurancePolicyNumber','DateOfIncide
nt'])
```

3.10 Scaling, without leaking, if necessary

This will depend on technique as tree based models for examples do not require scaling. However, scaling can be beneficial for other models such as SVM, k-NN, and neural networks. I will scale the numerical features as needed in the pipeline to ensure that all features are on the same scale.

```
df_num = X_train_filled.select_dtypes(include=[np.number])

df_num

       IncidentTime  NumberOfVehicles  BodilyInjuries  
AmountOfInjuryClaim  \
20936             4                 3               2               
10529
19307            19                 3               2               
4978
2609              8                 1               2               
347
15420             4                 2               2               
14503
21007            14                 1               0               
6367
...             ...               ...             ...               
...
27962            10                 3               0               
5591
10263            21                 3               2               
7590
11822            16                 3               0               
12538
8667             21                 3               0               
8729
10825            12                 1               2               
7589
```

```
       AmountOfPropertyClaim  AmountOfVehicleDamage  InsuredAge
CapitalGains  \
20936                   5901                  34135          44
0
19307                   4710                  43613          40
0
2609                     693                   2882          38
0
15420                  14503                  59684          33
45600
21007                  12735                  43169          47
0
...                      ...                    ...         ...
...
27962                  10472                  41889          39
0
10263                   4863                  33917          32
69200
11822                  11212                  48826          43
54600
8667                    8729                  38353          45
33500
10825                   5233                  28000          30
0

       CapitalLoss  Policy_Deductible  PolicyAnnualPremium
UmbrellaLimit  \
20936            0               1000              1072.38
0
19307       -40600               1000              1441.49
0
2609        -43400               1507              1046.00
0
15420       -61400                500              1216.26
3026658
21007       -55600               1181              1493.96
0
...            ...                ...                  ...
...
27962       -71700                500              1349.37
0
10263       -36900               2000              1438.39
0
11822       -45500                638               851.46
0
8667             0                663              1298.81
0
10825            0                500              1282.72
```

```
0

       IncidentMonth  IncidentDay  PolicyAgeDays  AgeAtIncident  \
20936              2           27           4526              7
19307              2            8           8092              9
2609               1           17           3922             14
15420              2           25           6974             11
21007              1           10           8370             10
...              ...          ...            ...            ...
27962              2           22            466              4
10263              2           25           2806             12
11822              1           14           4435             11
8667               2           16           7950             10
10825              1            3           7144              5

       IncidentAddress_freq
20936                    28
19307                    16
2609                     39
15420                    15
21007                    21
...                     ...
27962                    24
10263                    22
11822                    22
8667                     46
10825                    14

[23068 rows x 17 columns]
```

```python
#catergorical columns
df_cat = X_train_filled.select_dtypes(include=['object', 'category'])
df_cat
```

```
                 TypeOfIncident TypeOfCollission SeverityOfIncident  \
20936   Multi-vehicle Collision  Front Collision       Major Damage
19307   Multi-vehicle Collision   Side Collision       Minor Damage
2609              Vehicle Theft              NaN     Trivial Damage
15420   Multi-vehicle Collision   Side Collision         Total Loss
21007  Single Vehicle Collision   Side Collision       Minor Damage
...                         ...              ...                ...
27962   Multi-vehicle Collision   Side Collision       Major Damage
10263   Multi-vehicle Collision   Rear Collision       Major Damage
11822   Multi-vehicle Collision  Front Collision       Major Damage
8667    Multi-vehicle Collision  Front Collision       Minor Damage
10825  Single Vehicle Collision   Rear Collision       Minor Damage

      AuthoritiesContacted IncidentState IncidentCity
PropertyDamage  \
20936                 Fire        State4        City4            NaN
```

```
19307                  Other       State8       City7           NaN
2609                    None       State9       City2           NaN
15420                  Other       State5       City7           NaN
21007                   Fire       State7       City4            NO
...                      ...          ...         ...           ...
27962                  Other       State5       City5            NO
10263                 Police       State5       City2           YES
11822                  Other       State4       City3            NO
8667                  Police       State7       City5            NO
10825              Ambulance       State9       City2           YES

      Witnesses PoliceReport InsuredGender InsuredEducationLevel  \
20936         1          YES          MALE               Masters
19307         0          NaN          MALE                    MD
2609          2           NO          MALE               Masters
15420         0           NO          MALE                    JD
21007         0          NaN        FEMALE                    MD
...         ...          ...           ...                   ...
27962         3           NO          MALE                    MD
10263         0           NO        FEMALE               College
11822         3           NO          MALE                    MD
8667          2          YES          MALE               College
10825         2          NaN          MALE                    JD

       InsuredOccupation InsuredHobbies InsurancePolicyState  \
20936     prof-specialty         movies               State1
19307    protective-serv       sleeping               State2
2609    transport-moving    video-games               State1
15420    exec-managerial      paintball               State1
21007              sales       kayaking               State3
...                  ...            ...                  ...
27962  machine-op-inspct        camping               State3
10263       craft-repair      skydiving               State3
11822    priv-house-serv    board-games               State3
8667    transport-moving        dancing               State2
10825     prof-specialty       kayaking               State1

      Policy_CombinedSingleLimit InsuredRelationship VehicleMake  \
20936                    100/300             husband    Mercedes
19307                    100/300           own-child        Saab
```

```
2609                          500/1000             husband      Suburu
15420                          250/500      other-relative         BMW
21007                          100/300       not-in-family        Ford
...                                ...                 ...         ...
27962                          250/500                wife         BMW
10263                          100/300             husband    Mercedes
11822                          100/300           own-child       Dodge
8667                           100/500       not-in-family        Audi
10825                          100/300       not-in-family         BMW

         VehicleModel          Region
20936  Grand Cherokee      Tamil Nadu
19307              93     Maharashtra
2609        Forrestor      Tamil Nadu
15420              X5     Maharashtra
21007            Neon      Tamil Nadu
...               ...             ...
27962              M5  Madhya Pradesh
10263            E400      Tamil Nadu
11822             RAM      Tamil Nadu
8667               A3      Tamil Nadu
10825              X5     Maharashtra

[23068 rows x 19 columns]
```

```
distinct_values = df_cat.nunique()
distinct_values
```

```
TypeOfIncident                 4
TypeOfCollission               3
SeverityOfIncident             4
AuthoritiesContacted           4
IncidentState                  7
IncidentCity                   7
PropertyDamage                 2
Witnesses                      5
PoliceReport                   2
InsuredGender                  2
InsuredEducationLevel          7
InsuredOccupation             14
InsuredHobbies                20
InsurancePolicyState           3
Policy_CombinedSingleLimit     9
InsuredRelationship            6
VehicleMake                   15
VehicleModel                  39
Region                         3
dtype: int64
```

One-Hot Encoding

```
import pandas as pd

def one_hot_encode_for_fraud_analysis(df, target_col='ReportedFraud', 
drop_first=False):
    """
    One-hot encodes all categorical columns (object/category) in the 
DataFrame
    except for the specified target column, typically used in fraud 
analysis.

    Parameters

    df : pd.DataFrame
        The DataFrame containing both numeric and categorical columns.
    target_col : str, optional
        The name of the target column (e.g., 'ReportedFraud'). If this 
column
        is a string type and you do not want to one-hot encode it, 
specify it here.
        Default is 'ReportedFraud'.
    drop_first : bool, optional
        Whether to drop the first category in each encoded feature to 
avoid
        the dummy variable trap. Default is False.

    Returns

    pd.DataFrame
        A new DataFrame with the categorical features encoded except 
for the target column.

    """
    # Identify all object/category columns
    cat_cols = df.select_dtypes(include=["object", 
"category"]).columns.tolist()

    # Exclude the target column if in cat_cols
    if target_col in cat_cols:
        cat_cols.remove(target_col)

    # One-hot encode the remaining categorical columns
    df_encoded = pd.get_dummies(df, columns=cat_cols, 
drop_first=drop_first)

    return df_encoded

X_train_ohe = 
one_hot_encode_for_fraud_analysis(X_train_filled,drop_first=True)
```

```
X_test_ohe =
one_hot_encode_for_fraud_analysis(X_test_filled,drop_first=True)


print(X_train_ohe.shape)
print(X_test_ohe.shape)
```

```
(23068, 154)
(5768, 154)
```

Check Point

```
print(X_train_ohe.shape)
print(y_train.shape)

print(X_test_ohe.shape)
print(y_test.shape)

#previous resuls
# (92275, 40)
# (23069, 40)
# (92275,)
# (23069,)
```

```
(23068, 154)
(23068,)
(5768, 154)
(5768,)
```

Numbers are as expected. I can save the preprocessed data to a checkpoint file to avoid repeating the preprocessing steps in case of any issues. This will allow me to reload the preprocessed data and continue with the analysis without starting from scratch.

```
#checkpoint


X_train_ohe.to_csv('checkpoint/encoded_xtrain_checkpoint.csv', index =
False)
X_test_ohe.to_csv('checkpoint/encoded_xtest_checkpoint.csv', index =
False)

y_train.to_csv('checkpoint/encoded_ytrain_checkpoint.csv', index =
False)
y_test.to_csv('checkpoint/encoded_ytest_checkpoint.csv', index =
False)
```

4. Technique 1: P (Multi-Layer Perceptron)

4.1 Motivation for choosing the technique and schematic figure of the analysis process

```
from IPython.display import Image, display
import os
```

Rationale for Choosing a Multi-Layer Perceptron (MLP) for Binary Classification

I had tried a number of different models and found the MLP gave one of the best results. A Multi-Layer Perceptron (MLP) is well-suited for binary classification tasks because it can model complex, non-linear relationships between features and the target variable. By utilising multiple hidden layers and non-linear activation functions, MLPs can learn intricate decision boundaries that would be difficult to achieve with linear models alone.

MLPs also offer a high degree of flexibility and adaptability, allowing them to capture a wide range of data patterns without the need for extensive feature engineering. As a result, they can handle large datasets and high-dimensional feature spaces effectively, can be useful for fraud detection, where subtle anomalies may not follow simple patterns.

Building pipeline for the MLP

The pipeline consists of the following key components:

- Pipeline: built with scikit-learn

- Data Scaling (StandardScaler): normalises features to a mean of 0 and standard deviation of 1, helping the neural network converge faster by ensuring features are on a similar scale.

- Feature Selection (SelectKBest): uses an ANOVA F-test to remove less informative features, allowing the MLP to focus on the 20 most relevant inputs.

- Classifier (MLPClassifier): A Multi-Layer Perceptron with hidden layers of neurons and a ReLU activation function (see the next section for details).

- Early Stopping: prevents overfitting and saves time by halting training when the validation loss stops decreasing, capturing the minimal point on the learning curve. -Class Imbalance: as the MLP does not have built-in handling for class imbalance, the `imblearn` library (part of the scikit-learn contrib projects) is used.
  - SMOTE: creates synthetic samples of the minority class.

  - ClusterCentroids: undersamples the majority class.

MLP Scheme

The pipeline ensures the same scaling and feature selection steps are applied in every cross-validation fold during hyperparameter tuning. StratifiedKFold splits the data in a way that keeps class proportions the same, making the results fair. Finally, to handle uneven class sizes, we calculate class weights and use them in training so that the minority class is not overshadowed by the majority class.

```
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.feature_selection import RFE
from sklearn.decomposition import PCA, TruncatedSVD
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

y_train_mapped = y_train.map({'Y': 1, 'N': 0})
y_train_mapped.value_counts()

ReportedFraud
0    16840
1     6228
Name: count, dtype: int64

#map the target column to 1 and 0

y_test_mapped = y_test.map({'Y': 1, 'N': 0})
y_test_mapped.value_counts()

ReportedFraud
0    4211
1    1557
Name: count, dtype: int64

print(X_train_ohe.shape)
print(y_train_mapped.shape)

print(X_test_ohe.shape)
print(y_test_mapped.shape)

#previous resuls
# (92275, 40)
# (23069, 40)
# (92275,)
# (23069,)

(23068, 154)
(23068,)
(5768, 154)
(5768,)

X_train = X_train_ohe
y_train = y_train_mapped
```

```
X_test = X_test_ohe
y_test = y_test_mapped

import numpy as np
from sklearn.model_selection import train_test_split, StratifiedKFold,
GridSearchCV, cross_val_predict
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
from sklearn.utils.class_weight import compute_class_weight
```

4.2 Other items necessary for the technique

```
#pipeline
# Part of scikit learn
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as ImbPipeline
from imblearn.under_sampling import ClusterCentroids # for
undersampling to improve class balance

pipeline = ImbPipeline([
    ('smote', SMOTE(random_state=42)),  # Add SMOTE step
    #('undersample', ClusterCentroids(random_state=42)),  #
undersampling step
    ('scaler', StandardScaler()), # Scale features to have mean=0 and
variance=1
    ('feat_select', SelectKBest(score_func=f_classif, k=20)), # Select
the 20 best features based on ANOVA F-value
    ('clf', MLPClassifier( # Multi-layer Perceptron classifier
        random_state=42, # for reproducibility
        early_stopping=True, # stop training when performance worsens
on the validation set
        validation_fraction=0.2, # use 20% of the training data as
validation
        n_iter_no_change=5 # stop training if the validation score
doesn't improve for 5 iterations
    ))
])
```

4.3 Setting hyperparameters (rationale)

- param_grid: Set up to explore a range of hyperparameter values to optimise the performance of the Multi-Layer Perceptron (MLP) classifier within the pipeline. The chosen hyperparameters and their respective values are justified as follows:

- feat_select_k: The number of top features to select using SelectKBest. The step will try 10, or 20 or 30 features, and see which works best. Testing these values allows for identifying the subset of features that contribute most to the predictive power, reducing the risk of overfitting and improving computational efficiency.

- hidden_layer_sizes: This is the MLPClassifier (neural network) step. Each tuple represents the number of neural networks hidden layer; initially set to: (100,) - one hidden layer with 100 neurons. (100,50) - 2 hidden layers, one with 100 neaurons then another with 50 neaurons. (100,100) means 2 hidden layers, each with 100 neurons. These can be adjusted to create different shapes of the network to see which performs best. I will use a 3-layer architecture which is deep enough to capture complex patterns in the data without being too deep to cause overfitting.

- Regulisation: alpha (L2 regularisation): The regularisation parameter to prevent overfitting and penalising large weights. I will set this to [0.0001, 0.005, 0.01] to a weaker regulaisation so it can learn more complex patterns but may overfit. Exploring these alpha values allows for finding the right balance between fitting the training data and maintaining generalization to unseen data.

- learning_rate_init: The initial learning rate for is [0.001, 0.005, 0.01]. A higher rate can make the model faster but may overshoot the best solution; while a lower rate can help the model learn more carefully but may take longer to train.

By systematically tuning these hyperparameters, we aim to enhance the model's ability to generalise, achieve better performance metrics, and ensure robustness in fraud detection tasks.

```
param_grid = {
    'feat_select__k': [10, 20, 30], # Number of features to select
    'clf__hidden_layer_sizes': [(100,), (100, 50), (100, 100)], # Number of neurons in each hidden layer
    'clf__alpha': [0.001, 0.01, 0.5], # L2 penalty (regularisation term) parameter
    'clf__learning_rate_init': [0.001, 0.005, 0.01], # Initial learning rate
}
```

4.4 Dealing with class imbalance, if necessary, if not done above

```
# percentage of each class in y_train
fraud_train_counts = y_train.value_counts()
fraud_train_percent = y_train.value_counts(normalize=True) * 100
fraud_train_percent
```

```
ReportedFraud
0    73.001561
1    26.998439
Name: proportion, dtype: float64
```

Balanced class weights are needed to prevent the model from being biased towards the majority class. This is especially important in fraud detection tasks where the number of fraudulent claims is much lower than genuine claims. To address this issue, I have used imblearn in the pipeline as MLP doesnt have built-in handling for class imbalance and neither does a manual entry of class weights work.

```
# Code moved to pipeline
```

4.5 Optimising the Hyperparameters Appropriately

- Cross-Validation Strategy: stratified k-fold cross-validation with 3 splits to ensure that each fold maintains the class distribution of the original data. This will help to evaluate the model's performance across different subsets of the data and provide a more reliable estimate.

- GridSearchCV with MLPClassifier: Grid search with cross-validation will find the optimal hyperparameters for the MLP classifier by trying different combinations from the param_grid on the given pipeline. The accuracy metric is used to measure performance and cross valiidation is defined by the cv_strategy. Using this over the parameter grid, the model will be trained and evaluated on different hyperparameter combinations to identify the best configuration that maximises performance metrics. With n_jobs=-1, all CPU cores will be used to speed up the search.

- Grid_search.fit(X_train, y_train) splits the training data, trains the pipeline with every hyperparameter combination, measures accuracy, and selects the best-performing set of parameters.

```
# Cross-validation strategy
cv_strategy = StratifiedKFold(n_splits=3, shuffle=True,
random_state=42) # Stratified K-Fold CV

grid_search = GridSearchCV( # Grid search for hyperparameter tuning
    estimator=pipeline, # The pipeline to tune
    param_grid=param_grid, # The hyperparameter search space
    scoring='accuracy', # The metric to optimise
    cv=cv_strategy, # The cross-validation strategy
    n_jobs=-1, # Use all available CPU cores
    verbose=1,
)


#  Fit the grid search on the training data
grid_search.fit(X_train, y_train)

Fitting 3 folds for each of 81 candidates, totalling 243 fits

GridSearchCV(cv=StratifiedKFold(n_splits=3, random_state=42,
shuffle=True),
             estimator=Pipeline(steps=[('smote',
SMOTE(random_state=42)),
                                       ('scaler', StandardScaler()),
```

```
                                              ('feat_select',
SelectKBest(k=20)),
                                              ('clf',

MLPClassifier(early_stopping=True,

n_iter_no_change=5,
                                                              random_state=42,

validation_fraction=0.2))]),
             n_jobs=-1,
             param_grid={'clf__alpha': [0.001, 0.01, 0.5],
                         'clf__hidden_layer_sizes': [(100,), (100,
50),
                                                      (100, 100)],
                         'clf__learning_rate_init': [0.001, 0.005,
0.01],
                         'feat_select__k': [10, 20, 30]},
             scoring='accuracy', verbose=1)
```

4.5 Performance Metrics for Training Set

- Best parameters from grid search, shows the best cross-validated score, and the best estimator from the grid search. The best estimator is the model with the optimal hyperparameters that achieved the highest cross-validated score during grid search.

- Cross val prediction score obtains out of the box predictions from the cross-validated model. This allows us to evaluate the model's performance on the training set using the best hyperparameters identified during grid search.

```
print("Best Params:", grid_search.best_params_)
print("Best CV Score on Training Splits:", grid_search.best_score_)

y_val_pred = cross_val_predict(
    grid_search.best_estimator_, # The best pipeline from GridSearchCV

    X_train, # Training data
    y_train, # Target labels
    cv=cv_strategy, # Same CV strategy as GridSearchCV
    n_jobs=-1
)

best_model_mlp = grid_search.best_estimator_

accuracy = accuracy_score(y_train, y_val_pred) # Compute overall
accuracy
print(f"K-Fold Averaged Accuracy: {accuracy:.4f}")

class_report = classification_report(y_train, y_val_pred) # Generate
```

```
classification report
print("\nClassification Report:\n", class_report)
```

```
Best Params: {'clf__alpha': 0.01, 'clf__hidden_layer_sizes': (100, 100), 'clf__learning_rate_init': 0.005, 'feat_select__k': 30}
Best CV Score on Training Splits: 0.826512618891663
K-Fold Averaged Accuracy: 0.8265

Classification Report:
               precision    recall  f1-score   support

           0       0.87      0.90      0.88     16840
           1       0.70      0.62      0.66      6228

    accuracy                           0.83     23068
   macro avg       0.78      0.76      0.77     23068
weighted avg       0.82      0.83      0.82     23068
```

Classification Report from Training Set MLP

Best Hyperparameters: -clf__alpha': 0.01 - moderate level of L2 regulaisation on MLP

- clf__hidden_layer_sizes': (100, 100) - two hidden layers with 100 neurons each
- 'clf__learning_rate_init': 0.005, - moderate learning rate
- 'feat_select__k': 30 - 30 top features selected by SelectKBest

Best Cross-Validated Score: 0.8265

- On average, across multiple train/validation splits, this configuration correctly predicted the label about 82.65% of the time.

K-Fold Cross-Validation Score: 0.8265

- The model achieved an average accuracy of 82.65% across the training data using the best hyperparameters identified during grid search.

Classification Report:

- class 0 - precision = 0.87, recall = 0.90, f1-score = 0.88; the model is good at identifying Class 0 with predicts with correct 87% of the time and recalls 89% of the time.
- class 1 - precision = 0.70, recall = 0.62, f1-score = 0.66; the model is not as good at identifying Class 1 with predicts with correct 70% of the time and recalls 62% of the time.
- Overall Accuracy across both classes is 83%
- Weighted average (0.82 precision, 0.83 recall) accounts for the fact that Class 0 has more samples and thus carries more weight in the overall score.

- Overall the model achieves around 83% accuracy on the training dataset, performs very well on the majority class (Class 0), and is reasonably effective but less accurate for the minority class (Class 1).
- ('undersample', ClusterCentroids(random_state=42)), undersampling step was removed as it did not improve performance and also significantly increased the processing it.

5. Technique 2 - HistGradientBoostClassifier

5.1 Motivation for choosing the technique and schematic figure of the analysis process

For the binary classification problem, I chose a a tree-based gradient boosting approach and which uses an ensemble method. The HistGradientBoostingClassifier is preffered over the GradientBoostingClassifier, due to its efficiency of speed as it uses bins to group continuos features. It is also more memory efficient, is robust to outliers and can handle imbalanced datasets effectively. Scaling is not required for decision tree-based models, making it computationally efficient for large datasets. This makes it well-suited for binary classification tasks as it can handle complex relationships between features and the target variable, making it effective for fraud detection.

The schematic analysis flow is as follows:

Histogram Gradient Boosting Classifier

5.2 Other items necessary for the technique

Pipeline

```
from sklearn.pipeline import Pipeline
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.ensemble import HistGradientBoostingClassifier
from sklearn.model_selection import StratifiedKFold, GridSearchCV,
cross_val_predict
from sklearn.metrics import accuracy_score, classification_report


# 1) pipeline feature selection  HistGradientBoosting
pipeline = Pipeline([
    ('feat_select', SelectKBest(score_func=f_classif, k=20)),
    ('clf', HistGradientBoostingClassifier( # Gradient Boosting
classifier
        random_state=42, # for reproducibility
        early_stopping=True,       # built-in early stopping
        validation_fraction=0.2,   # use 20% of the training data as
validation set
        n_iter_no_change=5        # stop training if the validation
score doesn't improve for 5 iterations
```

```
    ))
])
```

5.3 Setting hyperparameters (rationale)

The hyperparameters for the HistGradientBoostingClassifier are chosen based on the following rationale:

- 'feat_select__k': [10, 20, 30] - I am looking for the top features to keep after the F-test in SelectKBest.I will test different values to identify the subset of features that contribute most to the predictive power. The aim is to find the sweet spot too many features can lead to overfitting, while too few features can lead to underfitting.

- clf__max_iter': [100, 200] - The maximum number of iterations for the gradient boosting classifier. I will test different values to find the optimal number of iterations for convergence. The aim is calancing compute time with thorough training. Higher accuracy can be achieved with more iterations, but it comes at the cost of increased computational time and potential overfitting.

- clf__learning_rate': [0.05, 0.1, 0.2] - The learning rate shrinks the contribution of each tree. I will test different values to control the impact of each tree on the final prediction. Lower valus can give better training, while higher values can be faster but risk overfitting.

- clf__max_depth': [None, 5] - The maximum depth of the decision trees. I will test different values to control the complexity of the trees and prevent overfitting. A limit of 5 can help prevent overfitting.

- clf__max_leaf_nodes': [31, 63] - The maximum number of leaf nodes in each tree. I will test different values to control the complexity of the trees and prevent overfitting. A limit of 31 can help prevent overfitting. A larger leaf count can lead to more complex trees and potential overfitting and become computationally inefficient.

```
# 2) hyperparameter search space
param_grid = {
    'feat_select__k': [10, 20, 30], # Number of features to select
    'clf__max_iter': [100, 200], # Maximum number of iterations
    'clf__learning_rate': [0.05, 0.1, 0.2], # Learning rate
    'clf__max_depth': [None, 5], # Maximum depth of the trees
    'clf__max_leaf_nodes': [31, 63], # Maximum number of leaf nodes
per tree

}
```

5.4 Optimising the Hyperparameters Appropriately

Cross Validation Strategy: The training data is split into 3 folds (subsets). Stratified makes each fold preserves the proportion of each class. Thhe data is shuffeled before splitting to make the folds more random. Setting a random_state (42) makes sure results are reproducible—if someone else runs the code, they'll get the same splits.The best hyperparameters are chosen based on the average score across the cross-validation folds.

GridSearchCV is used over the specified paramater grid to find the optimal hyperparameters for the HistGradientBoostingClassifier to tune the pipeline. Performance is measured by accuracy. . The grid search will train and evaluate the model on different hyperparameter combinations to identify the best configuration that maximises performance metrics. The final model is evaluated on the train set to assess its performance.

```
cv_strategy = StratifiedKFold(n_splits=3, shuffle=True,
random_state=42)
grid_search = GridSearchCV( # Grid search for hyperparameter tuning
    estimator=pipeline, # The pipeline to tune
    param_grid=param_grid, # The hyperparameter search space
    scoring='accuracy', # The metric to optimise
    cv=cv_strategy, # The cross-validation strategy
    n_jobs=-1, # Use all available CPU cores
    verbose=1 # Output progress
)
grid_search.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 72 candidates, totalling 216 fits
```

```
GridSearchCV(cv=StratifiedKFold(n_splits=3, random_state=42,
shuffle=True),
             estimator=Pipeline(steps=[('feat_select',
SelectKBest(k=20)),
                                       ('clf',

HistGradientBoostingClassifier(early_stopping=True,

n_iter_no_change=5,

random_state=42,

validation_fraction=0.2))]),
             n_jobs=-1,
             param_grid={'clf__learning_rate': [0.05, 0.1, 0.2],
                         'clf__max_depth': [None, 5],
                         'clf__max_iter': [100, 200],
                         'clf__max_leaf_nodes': [31, 63],
                         'feat_select__k': [10, 20, 30]},
             scoring='accuracy', verbose=1)
```

5.5 Performance metrics for training set

```
print("Best Params:", grid_search.best_params_)
print("Best CV Score on Training Splits:", grid_search.best_score_)

y_val_pred = cross_val_predict(
    grid_search.best_estimator_, # The best pipeline from GridSearchCV

    X_train, # Training data
    y_train, # Target labels
    cv=cv_strategy, # Same CV strategy as GridSearchCV
    n_jobs=-1
)

best_model_hgb = grid_search.best_estimator_

accuracy = accuracy_score(y_train, y_val_pred) # Compute overall
accuracy
print(f"K-Fold Averaged Accuracy: {accuracy:.4f}")

class_report = classification_report(y_train, y_val_pred) # Generate
classification report
print("\nClassification Report:\n", class_report)
```

```
Best Params: {'clf__learning_rate': 0.1, 'clf__max_depth': None,
'clf__max_iter': 200, 'clf__max_leaf_nodes': 63, 'feat_select__k': 30}
Best CV Score on Training Splits: 0.8755854080973934
K-Fold Averaged Accuracy: 0.8756

Classification Report:
               precision    recall  f1-score   support

           0       0.89      0.94      0.92     16840
           1       0.82      0.70      0.75      6228

    accuracy                           0.88     23068
   macro avg       0.85      0.82      0.83     23068
weighted avg       0.87      0.88      0.87     23068
```

Classification Report for Training Set HGB

1. **Best Hyperparameters**
   - clf__learning_rate = 0.1: The model's learning rate is 0.1, balancing how quickly it learns.
   - clf__max_depth = None: The model's trees can grow without a predefined maximum depth (they can become quite deep if needed).
   - clf__max_iter = 200: Up to 200 boosting stages (iterations) are allowed.

    - clf__max_leaf_nodes = 63: Each tree can have at most 63 leaf nodes.

    - feat_select__k = 30: The model is using the top 30 features, as selected by SelectKBest.

2. **Best Cross-Validation Score**
    - 0.875585... (about 87.56%).

    - This means that, on average, across the cross-validation folds, the model correctly classified about 87.56% of instances with the best hyperparameter settings.

3. **K-Fold Averaged Accuracy**
    - 0.8756 (nearly 87.56).

    - When we look at the predictions over the entire training set using cross-validation, the model is again correct about 87.56% of the time, which is consistent with the best CV score.

4. **Classification Report**
    - Overall Accuracy: 0.88 or 88% (slightly rounded).

    - Class 0:
        - Precision: 0.89 (when predicting class 0, it's right 89% of the time).

        - Recall: 0.94 (out of all actual class 0 samples, it correctly identifies 94%).

        - F1-score: 0.92 (balanced measure of precision and recall).

    - Class 1:
        - Precision: 0.82 (when predicting class 1, it's right 82% of the time).

        - Recall: 0.70 (it catches 70% of the true class 1 instances).

        - F1-score: 0.75.

    - The model clearly performs better on class 0 (the majority class) than on class 1, shown by higher recall and precision for class 0.

    - Macro Average (0.85 precision, 0.82 recall, 0.83 F1) treats both classes equally.

    - Weighted Average (0.87 precision, 0.88 recall, 0.87 F1) accounts for the fact that there are more class 0 samples, so the overall score is skewed toward class 0's strong performance.

Summary:

- The model is quite accurate overall (~88%).

- It classifies class 0 more confidently and more often correctly than class 1. This is typical when the dataset is imbalanced, but still, an F1-score of 0.75 for class 1 indicates a reasonably good performance for the minority class.

1. MLPClassifier Performance

Test Accuracy: 0.860957
Balanced Accuracy: 0.800743

Classification Report

Class	Precision	Recall	F1-score	Support
N	0.88	0.93	0.91	4211
Y	0.78	0.67	0.72	1557
Accuracy			**0.86**	**5768**
Macro Avg	**0.83**	**0.80**	**0.81**	**5768**
Weighted Avg	**0.86**	**0.86**	**0.86**	**5768**

Confusion Matrix

	Predicted N	Predicted Y
Actual N	3923	288
Actual Y	514	1043

2. HistGradientBoostingClassifier Performance

Test Accuracy: 0.868412
Balanced Accuracy: 0.814551

Classification Report

Class	Precision	Recall	F1-score	Support
N	0.89	0.93	0.91	4211
Y	0.79	0.70	0.74	1557
Accuracy			**0.87**	**5768**
Macro Avg	**0.84**	**0.81**	**0.83**	**5768**
Weighted Avg	**0.87**	**0.87**	**0.87**	**5768**

Confusion Matrix

	Predicted N	Predicted Y
Actual N	3923	288
Actual Y	471	1086

Summary Comparison

Metric	MLPClassifier	HistGradientBoostingClassifier
Test Accuracy	86.10%	86.84%
Balanced Accuracy	80.07%	81.46%
Precision (N)	0.88	0.89
Precision (Y)	0.78	0.79
Recall (N)	0.93	0.93
Recall (Y)	0.67	0.70
F1-score (N)	0.91	0.91
F1-score (Y)	0.72	0.74
Support (N)	4211	4211
Support (Y)	1557	1557
Overall Accuracy	0.86	0.87

Observations

- **Test Accuracy:** Both models perform similarly, with the HistGradientBoostingClassifier having a slight edge.
- **Balanced Accuracy:** HistGradientBoostingClassifier shows better balanced accuracy, indicating improved performance on minority classes.
- **Precision & Recall:** Both models have high precision and recall for class 'N' ("No Fraud"). The Gradient Boosting model slightly outperforms the MLPClassifier in precision and recall for class 'Y' ("Fraud").
- **F1-score:** The Gradient Boosting model has a marginally higher F1-score for class 'Y', suggesting better balance between precision and recall.
- **Confusion Matrix:** The Gradient Boosting model correctly identifies more fraud cases (higher true positives) while maintaining a similar number of false positives compared to the MLPClassifier.

These tables provide a comprehensive overview of the performance metrics for both classifiers, facilitating an informed comparison to determine which model better suits your objectives, especially concerning fraud detection.

6 Comparing the Two Techniques

- Use of nested cross-validation for both techniques to deal with overfitting model selection and model comparison
- Use appropriate metrics for the testing set
- Use an appropriate model selection visualisation curve (ROC, PR, etc.) that is suitable for the problem at hand
- Checking for overfitting

6.1 Use of Nested Cross-Validation

I will use set up a nested cross-validation to evaluate the performance of both models on the test set. This will help to ensure that the models are robust and generalise well to unseen data. I will use the same metrics as before to evaluate the models and compare their performance. This will include:

1. Two pipelines for the MLPClassifier and HistGradientBoostingClassifier.
2. Hyperparameter tuning using GridSearchCV.
3. Define Outer CV (5 folds) and Inner CV (3 folds) for nested cross-validation.
4. Split data into train_outer and test_outer

5. Inner CV: Grid search over hyperparameters for each model.
6. Evaluate the best models from each technique on the test_outer set.
7. Calculate and compare performance metrics for both models on the test set.

```
import numpy as np
from sklearn.model_selection import StratifiedKFold,
RandomizedSearchCV
from sklearn.pipeline import Pipeline
from sklearn.neural_network import MLPClassifier
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.metrics import accuracy_score
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as ImbPipeline
from sklearn.ensemble import HistGradientBoostingClassifier

# Example pipeline for HGB: feature selection +
HistGradientBoostingClassifier
pipeline_hgb = Pipeline([
    ('feat_select', SelectKBest(score_func=f_classif)),
    ('clf', HistGradientBoostingClassifier(random_state=42,
early_stopping=True, validation_fraction=0.1))
])

# Example hyperparameter distributions for HGB
param_distributions_hgb = {
    'feat_select__k': [10, 20, 30],
    'clf__max_iter': [100, 200],
    'clf__learning_rate': [0.05, 0.1, 0.2],
    'clf__max_depth': [None, 5],
    'clf__max_leaf_nodes': [31, 63]
}

# Outer cross-validation strategy (for model evaluation)
outer_cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Inner cross-validation strategy (for hyperparameter tuning)
inner_cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
```

```python
# Initialize lists to store outer scores and best models
outer_scores = []  # To store scores of the outer loop
best_models = []  # To store best models for each fold

# Nested cross-validation: iterate through outer folds
for train_idx, val_idx in outer_cv.split(X_train, y_train):
    # Split data into train and test for the outer loop
    X_train_curr, X_val_curr = X_train.iloc[train_idx],
X_train.iloc[val_idx]
    y_train_curr, y_val_curr = y_train.iloc[train_idx],
y_train.iloc[val_idx]

    # Randomized search in the inner loop for hyperparameter tuning
    grid_search = RandomizedSearchCV(
        estimator=pipeline_hgb,
        param_distributions=param_distributions_hgb,
        scoring='accuracy',
        cv=inner_cv,
        n_jobs=-1,
        verbose=1
    )

    # Fit the grid search on the inner training set
    grid_search.fit(X_train_curr, y_train_curr)

    # Evaluate the best model on the outer validation set
    best_model = grid_search.best_estimator_
    y_pred = best_model.predict(X_val_curr)
    outer_score = accuracy_score(y_val_curr, y_pred)

    # Append outer score and model to the lists
    outer_scores.append(outer_score)
    best_models.append(best_model)

    print(f"Outer fold score: {outer_score:.4f}")
    print(f"Best hyperparameters for this fold:
{grid_search.best_params_}")

# Report final nested cross-validation score
print(f"Nested CV Accuracy: {np.mean(outer_scores):.4f} ±
{np.std(outer_scores):.4f}")

# Identify the best model based on outer fold performance
best_outer_fold_idx = np.argmax(outer_scores)
best_model_from_outer_hgb = best_models[best_outer_fold_idx]

print(f"Best model (based on outer fold score):
{best_model_from_outer_hgb}")
print(f"Best outer fold score:
{outer_scores[best_outer_fold_idx]:.4f}")
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

Outer fold score: 0.8825
Best hyperparameters for this fold: {'feat_select__k': 30,
'clf__max_leaf_nodes': 63, 'clf__max_iter': 200, 'clf__max_depth':
None, 'clf__learning_rate': 0.05}
Fitting 5 folds for each of 10 candidates, totalling 50 fits
Outer fold score: 0.8680
Best hyperparameters for this fold: {'feat_select__k': 30,
'clf__max_leaf_nodes': 63, 'clf__max_iter': 200, 'clf__max_depth': 5,
'clf__learning_rate': 0.2}
Fitting 5 folds for each of 10 candidates, totalling 50 fits
Outer fold score: 0.8723
Best hyperparameters for this fold: {'feat_select__k': 30,
'clf__max_leaf_nodes': 31, 'clf__max_iter': 200, 'clf__max_depth':
None, 'clf__learning_rate': 0.1}
Fitting 5 folds for each of 10 candidates, totalling 50 fits
Outer fold score: 0.8762
Best hyperparameters for this fold: {'feat_select__k': 30,
'clf__max_leaf_nodes': 63, 'clf__max_iter': 200, 'clf__max_depth':
None, 'clf__learning_rate': 0.2}
Fitting 5 folds for each of 10 candidates, totalling 50 fits
Outer fold score: 0.8760
Best hyperparameters for this fold: {'feat_select__k': 30,
'clf__max_leaf_nodes': 63, 'clf__max_iter': 200, 'clf__max_depth': 5,
'clf__learning_rate': 0.1}
Nested CV Accuracy: 0.8750 ± 0.0048
Best model (based on outer fold score):
Pipeline(steps=[('feat_select', SelectKBest(k=30)),
                ('clf',
                 HistGradientBoostingClassifier(early_stopping=True,
                                                learning_rate=0.05,
                                                max_iter=200,
max_leaf_nodes=63,
                                                random_state=42))])
Best outer fold score: 0.8825

# Example: Pipeline for MLP
pipeline_mlp = ImbPipeline([
    ('smote', SMOTE(random_state=42)),  # Add SMOTE step
    #('undersample', ClusterCentroids(random_state=42)),  #
undersampling step
    ('scaler', StandardScaler()), # Scale features to have mean=0 and
variance=1
    ('feat_select', SelectKBest(score_func=f_classif)),
    ('clf', MLPClassifier(random_state=42, early_stopping=True,
validation_fraction=0.1))
])

# Hyperparameter distributions for MLP (renamed from 'param_grid_mlp')
```

```
param_distributions_mlp = {
    'feat_select__k': [10, 20, 30],  # Number of features to select
    'clf__hidden_layer_sizes': [(100,), (100, 50), (100, 100)],
    'clf__alpha': [0.001, 0.01, 0.5],
    'clf__learning_rate_init': [0.001, 0.005, 0.01]
}

# Outer cross-validation strategy (for model evaluation)
outer_cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Inner cross-validation strategy (for hyperparameter tuning)
inner_cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Initialize lists to store outer scores and best models
outer_scores = []  # To store scores of the outer loop
best_models = []  # To store best models for each fold

# Nested cross-validation: iterate through outer folds
for train_idx, val_idx in outer_cv.split(X_train, y_train):
    # Split data into train and test for the outer loop
    X_train_curr, X_val_curr = X_train.iloc[train_idx],
X_train.iloc[val_idx]
    y_train_curr, y_val_curr = y_train.iloc[train_idx],
y_train.iloc[val_idx]

    # Randomized search in the inner loop for hyperparameter tuning
    grid_search = RandomizedSearchCV(
        estimator=pipeline_mlp,
        param_distributions=param_distributions_mlp,
        scoring='accuracy',
        cv=inner_cv,
        n_jobs=-1,
        verbose=1
    )

    # Fit the grid search on the inner training set
    grid_search.fit(X_train_curr, y_train_curr)

    # Evaluate the best model on the outer validation set
    best_model = grid_search.best_estimator_
    y_pred = best_model.predict(X_val_curr)
    outer_score = accuracy_score(y_val_curr, y_pred)

    # Append outer score and model to the lists
    outer_scores.append(outer_score)
    best_models.append(best_model)

    print(f"Outer fold score: {outer_score:.4f}")
    print(f"Best hyperparameters for this fold:
{grid_search.best_params_}")
```

```python
# Report final nested cross-validation score
print(f"Nested CV Accuracy: {np.mean(outer_scores):.4f} ±
{np.std(outer_scores):.4f}")

# Identify the best model based on outer fold performance
best_outer_fold_idx = np.argmax(outer_scores)
best_model_from_outer_mlp = best_models[best_outer_fold_idx]

print(f"Best model (based on outer fold score):
{best_model_from_outer_mlp}")
print(f"Best outer fold score:
{outer_scores[best_outer_fold_idx]:.4f}")
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
Outer fold score: 0.8251
Best hyperparameters for this fold: {'feat_select__k': 30,
'clf__learning_rate_init': 0.01, 'clf__hidden_layer_sizes': (100, 50),
'clf__alpha': 0.01}
Fitting 5 folds for each of 10 candidates, totalling 50 fits
Outer fold score: 0.8244
Best hyperparameters for this fold: {'feat_select__k': 30,
'clf__learning_rate_init': 0.01, 'clf__hidden_layer_sizes': (100, 50),
'clf__alpha': 0.01}
Fitting 5 folds for each of 10 candidates, totalling 50 fits
Outer fold score: 0.8147
Best hyperparameters for this fold: {'feat_select__k': 30,
'clf__learning_rate_init': 0.01, 'clf__hidden_layer_sizes': (100, 50),
'clf__alpha': 0.001}
Fitting 5 folds for each of 10 candidates, totalling 50 fits
Outer fold score: 0.8229
Best hyperparameters for this fold: {'feat_select__k': 30,
'clf__learning_rate_init': 0.001, 'clf__hidden_layer_sizes': (100,),
'clf__alpha': 0.01}
Fitting 5 folds for each of 10 candidates, totalling 50 fits
Outer fold score: 0.8240
Best hyperparameters for this fold: {'feat_select__k': 30,
'clf__learning_rate_init': 0.005, 'clf__hidden_layer_sizes': (100,
50), 'clf__alpha': 0.001}
Nested CV Accuracy: 0.8222 ± 0.0038
Best model (based on outer fold score): Pipeline(steps=[('smote',
SMOTE(random_state=42)), ('scaler', StandardScaler()),
                ('feat_select', SelectKBest(k=30)),
                ('clf',
                 MLPClassifier(alpha=0.01, early_stopping=True,
                               hidden_layer_sizes=(100, 50),
                               learning_rate_init=0.01,
random_state=42))])
Best outer fold score: 0.8251
```

6.2 Use appropriate metrics for the testing set

```
best_model_mlp = best_model_from_outer_mlp

best_model_hgb = best_model_from_outer_hgb

## Evaluation on MLP on TEST SET

y_test_pred_mlp = best_model_mlp.predict(X_test)

# Accuracy
acc = accuracy_score(y_test, y_test_pred_mlp)
print(f"Test Accuracy (MLP): {acc:.4f}")

# Classification report (precision, recall, F1, support)
print("Classification Report (MLP):")
print(classification_report(y_test, y_test_pred_mlp))

# Confusion matrix
print("Confusion Matrix (MLP):")
print(confusion_matrix(y_test, y_test_pred_mlp))
```

```
Test Accuracy (MLP): 0.8225
Classification Report (MLP):
              precision    recall  f1-score   support

           0       0.87      0.89      0.88      4211
           1       0.69      0.63      0.66      1557

    accuracy                           0.82      5768
   macro avg       0.78      0.76      0.77      5768
weighted avg       0.82      0.82      0.82      5768

Confusion Matrix (MLP):
[[3761  450]
 [ 574  983]]
```

```
# Evaluation on HGB on TEST SET

y_test_pred_hgb = best_model_hgb.predict(X_test)

# Accuracy
acc = accuracy_score(y_test, y_test_pred_hgb)
print(f"Test Accuracy (HGB): {acc:.4f}")

# Classification report (precision, recall, F1, support)
print("Classification Report (HGB):")
print(classification_report(y_test, y_test_pred_hgb))

# Confusion matrix
print("Confusion Matrix (HGB):")
```

```
print(confusion_matrix(y_test, y_test_pred_hgb))
```

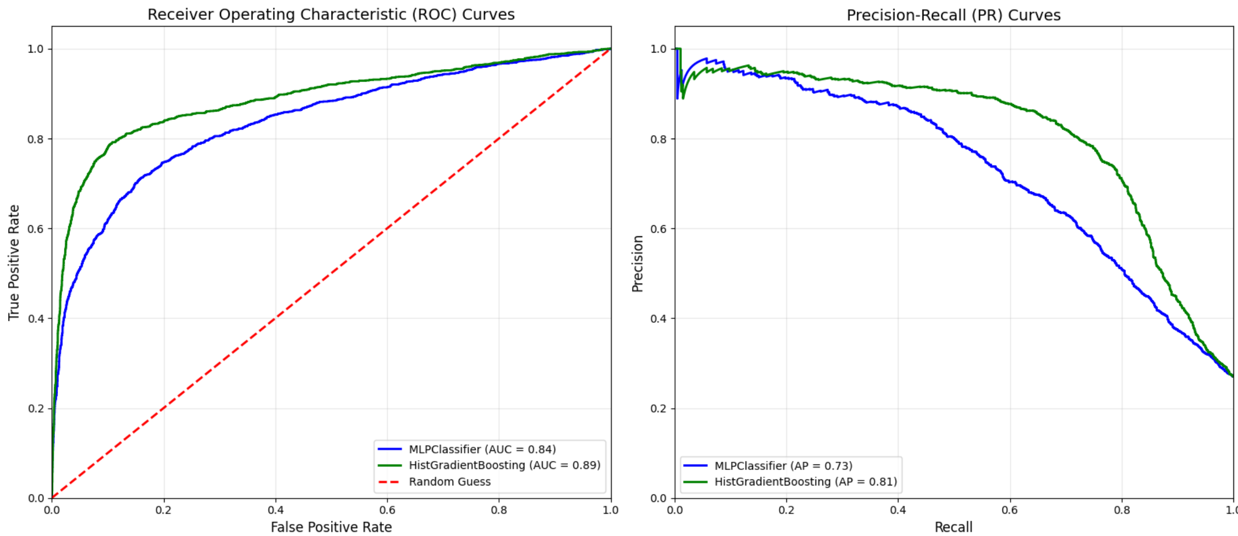
```
Test Accuracy (HGB): 0.8774
Classification Report (HGB):
              precision    recall  f1-score   support

           0       0.89      0.94      0.92      4211
           1       0.82      0.70      0.75      1557

    accuracy                           0.88      5768
   macro avg       0.86      0.82      0.84      5768
weighted avg       0.87      0.88      0.87      5768

Confusion Matrix (HGB):
[[3978  233]
 [ 474 1083]]
```

For analysis, please see section 7.1 Technical Perspective

6.3 Appropriate Model Selection Visualisation Curves

```
from sklearn.metrics import roc_curve, auc, precision_recall_curve,
average_precision_score

y_proba_mlp = best_model_mlp.predict_proba(X_test)[:, 1]
y_proba_hgb = best_model_hgb.predict_proba(X_test)[:, 1]



# Compute ROC curve and ROC area for MLP
fpr_mlp, tpr_mlp, _ = roc_curve(y_test_mapped, y_proba_mlp)
roc_auc_mlp = auc(fpr_mlp, tpr_mlp)

# Compute ROC curve and ROC area for HistGradientBoostingClassifier
fpr_gb, tpr_gb, _ = roc_curve(y_test_mapped, y_proba_hgb)
roc_auc_gb = auc(fpr_gb, tpr_gb)

# Compute Precision-Recall curve and average precision for MLP
precision_mlp, recall_mlp, _ = precision_recall_curve(y_test_mapped,
y_proba_mlp)
avg_precision_mlp = average_precision_score(y_test_mapped,
y_proba_mlp)

# Compute Precision-Recall curve and average precision for
HistGradientBoostingClassifier
precision_gb, recall_gb, _ = precision_recall_curve(y_test_mapped,
y_proba_hgb)
```

```python
avg_precision_gb = average_precision_score(y_test_mapped, y_proba_hgb)

# Create subplots for ROC and Precision-Recall curves
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16, 7))

# Plot ROC curves
ax1.plot(fpr_mlp, tpr_mlp, color='blue', lw=2, label=f'MLPClassifier
(AUC = {roc_auc_mlp:.2f})')
ax1.plot(fpr_gb, tpr_gb, color='green', lw=2,
label=f'HistGradientBoosting (AUC = {roc_auc_gb:.2f})')
ax1.plot([0, 1], [0, 1], color='red', lw=2, linestyle='--',
label='Random Guess')
ax1.set_xlim([0.0, 1.0])
ax1.set_ylim([0.0, 1.05])
ax1.set_xlabel('False Positive Rate', fontsize=12)
ax1.set_ylabel('True Positive Rate', fontsize=12)
ax1.set_title('Receiver Operating Characteristic (ROC) Curves',
fontsize=14)
ax1.legend(loc="lower right", fontsize=10)
ax1.grid(alpha=0.3)

# Plot Precision-Recall curves
ax2.plot(recall_mlp, precision_mlp, color='blue', lw=2,
label=f'MLPClassifier (AP = {avg_precision_mlp:.2f})')
ax2.plot(recall_gb, precision_gb, color='green', lw=2,
label=f'HistGradientBoosting (AP = {avg_precision_gb:.2f})')
ax2.set_xlim([0.0, 1.0])
ax2.set_ylim([0.0, 1.05])
ax2.set_xlabel('Recall', fontsize=12)
ax2.set_ylabel('Precision', fontsize=12)
ax2.set_title('Precision-Recall (PR) Curves', fontsize=14)
ax2.legend(loc="lower left", fontsize=10)
ax2.grid(alpha=0.3)

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

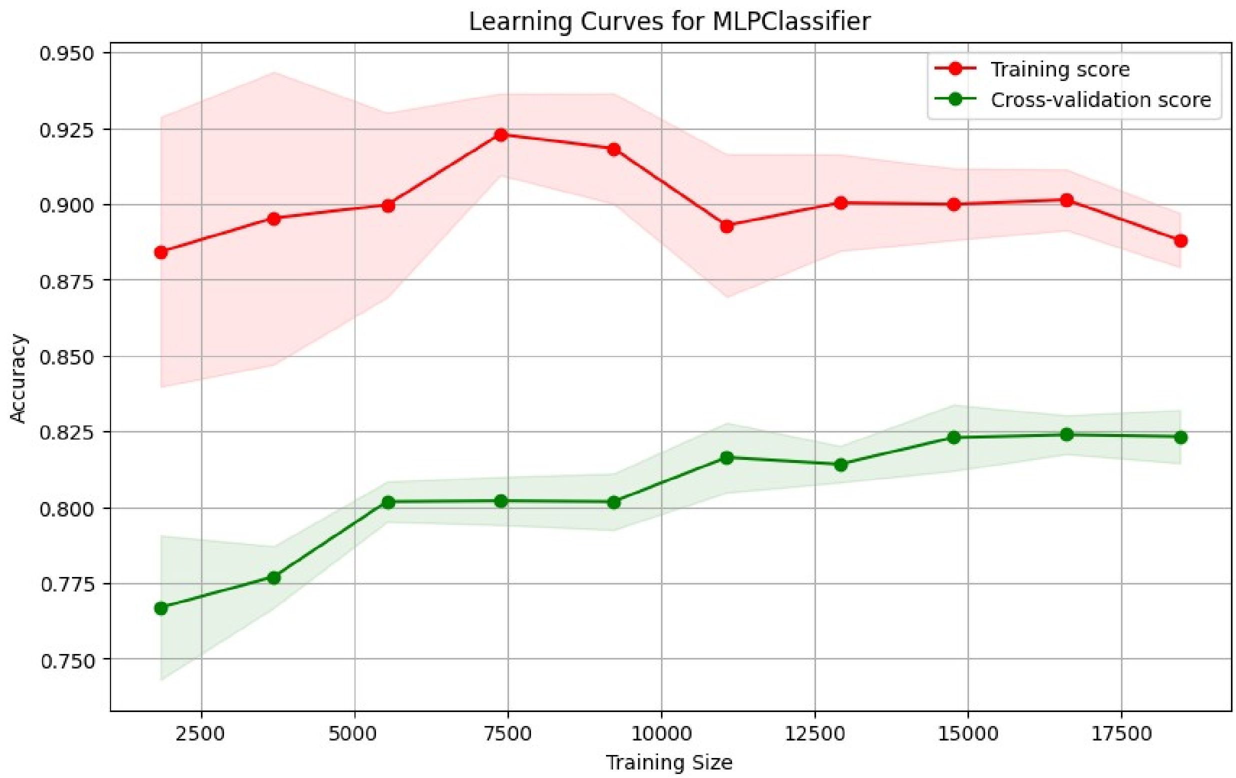


For analysis, please see section 7.1 Technical Perspective

6.4 Checking for Overfitting

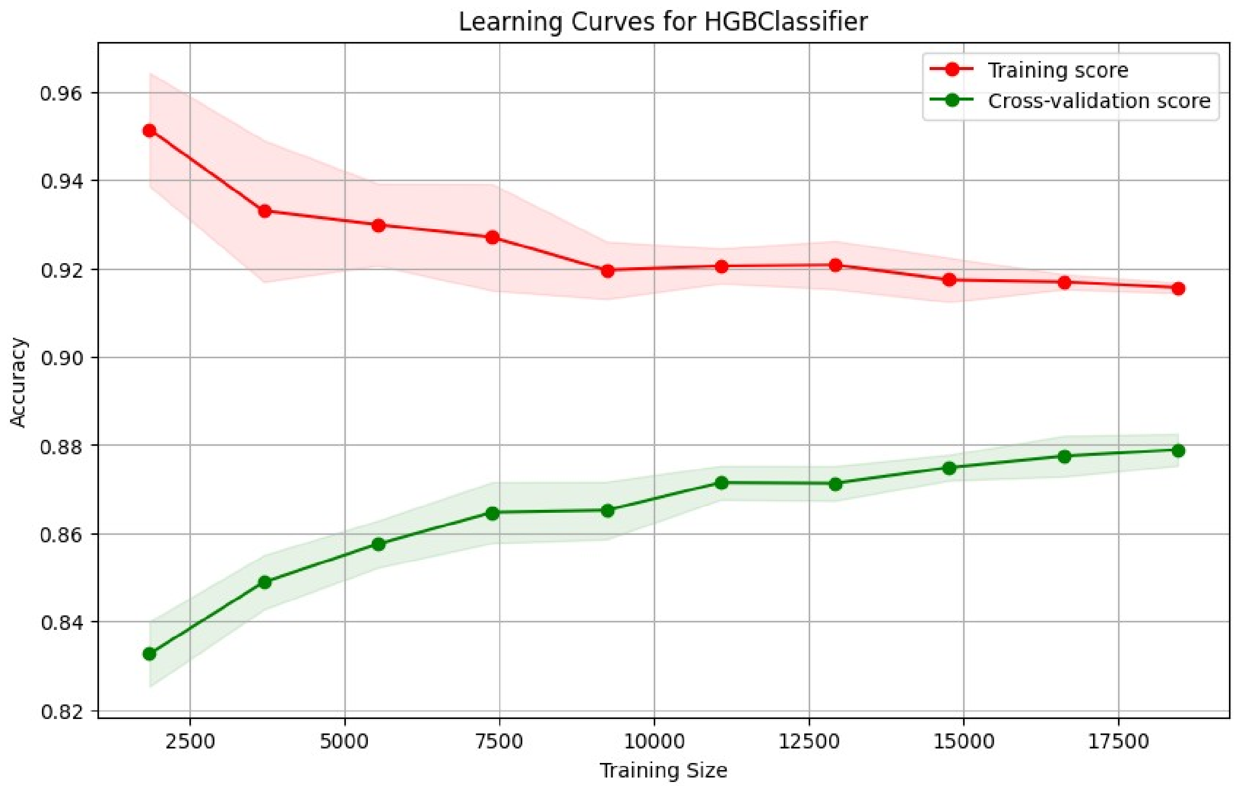
```
from sklearn.model_selection import learning_curve


# Define cross-validation strategy
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Generate learning curve
train_sizes, train_scores, val_scores = learning_curve(
    best_model_mlp, X_train, y_train, cv=cv, scoring='accuracy',
    train_sizes=np.linspace(0.1, 1.0, 10), n_jobs=-1)

# Calculate mean and std
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
val_scores_mean = np.mean(val_scores, axis=1)
val_scores_std = np.std(val_scores, axis=1)

# Plotting
plt.figure(figsize=(10, 6))
plt.plot(train_sizes, train_scores_mean, 'o-', color='r',
label='Training score')
plt.plot(train_sizes, val_scores_mean, 'o-', color='g', label='Cross-
validation score')
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
color='r')
plt.fill_between(train_sizes, val_scores_mean - val_scores_std,
                 val_scores_mean + val_scores_std, alpha=0.1,
color='g')
plt.title('Learning Curves for MLPClassifier')
```

```
plt.xlabel('Training Size')
plt.ylabel('Accuracy')
plt.legend(loc='best')
plt.grid()
plt.show()
```




```
# Define cross-validation strategy
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Generate learning curve
train_sizes, train_scores, val_scores = learning_curve(
    best_model_hgb, X_train, y_train, cv=cv, scoring='accuracy',
    train_sizes=np.linspace(0.1, 1.0, 10), n_jobs=-1)

# Calculate mean and std
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
val_scores_mean = np.mean(val_scores, axis=1)
val_scores_std = np.std(val_scores, axis=1)

# Plotting
plt.figure(figsize=(10, 6))
plt.plot(train_sizes, train_scores_mean, 'o-', color='r',
label='Training score')
```

```
plt.plot(train_sizes, val_scores_mean, 'o-', color='g', label='Cross-validation score')
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
color='r')
plt.fill_between(train_sizes, val_scores_mean - val_scores_std,
                 val_scores_mean + val_scores_std, alpha=0.1,
color='g')
plt.title('Learning Curves for HGBClassifier')
plt.xlabel('Training Size')
plt.ylabel('Accuracy')
plt.legend(loc='best')
plt.grid()
plt.show()
```



For discussion on overfitting, please see section 7.1 Technical Perspective

7. Final recommendation of the best model

7.1 Technical perspective- overfitting discussion, complexity and efficiency

7.1.1 Performance and Metrices

1. Overall Accuracy

- MLP: 0.8225 (about 82.25%)
- HGB: 0.8774 (about 87.74%)

From this, HGB is outperforming MLP in terms of simple accuracy.

2. Classification Report Details

MLP

- Class 0 - No Fraud:
  - Precision: 0.87
  - Recall: 0.89 (the model correctly identifies 89% of the “Class 0” cases)
  - F1-score: 0.88 - overall good performance
- Class 1 Fraud:
  - Precision: 0.69
  - Recall: 0.63 (the model correctly identifies 63% of the “Class 1” cases)
  - F1-score: 0.66 - overall score of precision and recall is lower

Overall, MLP tends to do better on Class 0, but struggles more with Class 1.

HGB

- Class 0:
  - Precision: 0.89
  - Recall: 0.94 (the model correctly identifies 94% of the “Class 0” cases)
  - F1-score: 0.92
- Class 1:
  - Precision: 0.82
  - Recall: 0.70 (the model correctly identifies 70% of the “Class 1” cases)
  - F1-score: 0.75

HGB shows stronger performance for both classes overall—particularly it does a better job on Class 1 compared to MLP.

3. Confusion Matrices

MLP

- 3761: True negatives (Class 0 correctly identified)

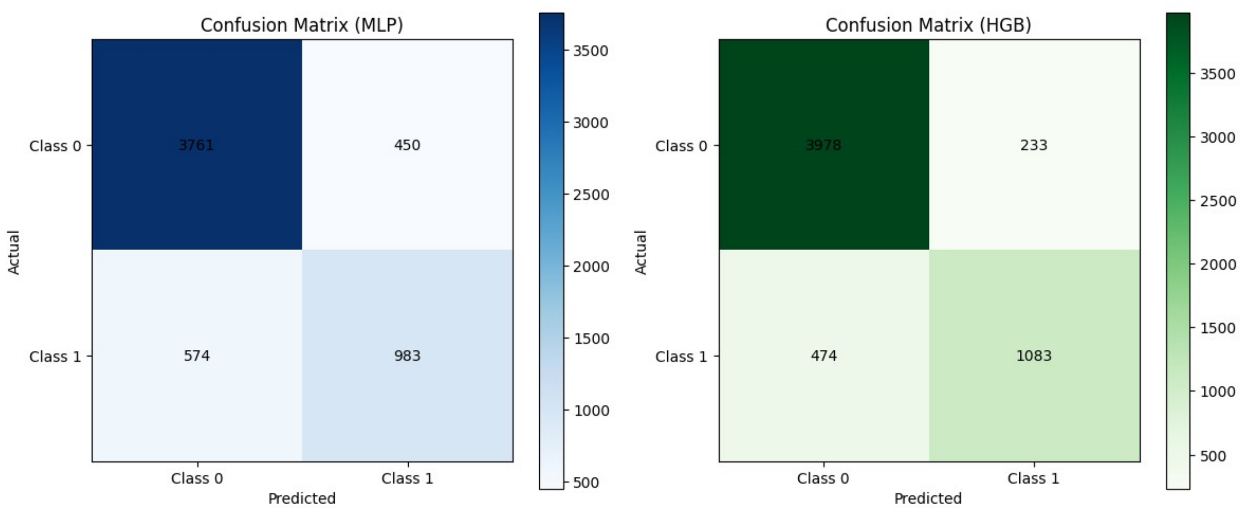
- 450: False positives (Class 1 was predicted when it was actually 0)
- *574: False negatives (Class 0 was predicted when it was actually 1)*
- 983: True positives (Class 1 correctly identified)

HGB

- 3978: True negatives (Class 0 correctly identified)
- 233: False positives (Class 1 was predicted when it was actually 0)
- *474: False negatives (Class 0 was predicted when it was actually 1)*
- 1083: True positives (Class 1 correctly identified)

```
#Confusion matrix values
cm_mlp = np.array([
    [3761, 450],
    [574,  983]
])

cm_hgb = np.array([
    [3978, 233],
    [474,  1083]
])


class_names = ['Class 0', 'Class 1']

# Create subplots
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))

#  Plot for MLP
im1 = axes[0].imshow(cm_mlp, interpolation='nearest', cmap='Blues')
axes[0].set_title("Confusion Matrix (MLP)")
axes[0].set_xlabel("Predicted")
axes[0].set_ylabel("Actual")

# Set up ticks & labels for MLP heatmap
axes[0].set_xticks(np.arange(len(class_names)))
axes[0].set_yticks(np.arange(len(class_names)))
axes[0].set_xticklabels(class_names)
axes[0].set_yticklabels(class_names)

# Annotate cells
for i in range(cm_mlp.shape[0]):
    for j in range(cm_mlp.shape[1]):
```

```python
        axes[0].text(j, i, cm_mlp[i, j],
                     ha="center", va="center", color="black")


fig.colorbar(im1, ax=axes[0])

# Plot for HGB
im2 = axes[1].imshow(cm_hgb, interpolation='nearest', cmap='Greens')
axes[1].set_title("Confusion Matrix (HGB)")
axes[1].set_xlabel("Predicted")
axes[1].set_ylabel("Actual")

# Set up ticks & labels for HGB heatmap
axes[1].set_xticks(np.arange(len(class_names)))
axes[1].set_yticks(np.arange(len(class_names)))
axes[1].set_xticklabels(class_names)
axes[1].set_yticklabels(class_names)

# Annotate cells
for i in range(cm_hgb.shape[0]):
    for j in range(cm_hgb.shape[1]):
        axes[1].text(j, i, cm_hgb[i, j],
                     ha="center", va="center", color="black")


fig.colorbar(im2, ax=axes[1])

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



Comparing the matrices:

- HGB has fewer false positives (233 vs. 450) and fewer false negatives (474 vs. 574) than MLP.

- That means HGB is doing a better job of correctly labeling both Class 0 and Class 1 instances.
- In terms of fraud detection, the false negatives are more critical as they represent missed fraudulent claims. The false positives on the other hand are less critical as they represent genuine claims that were incorrectly flagged as fraudulent; these can be further investigated for verification.

7.1.2 Learning Curves & Overfitting

Learning Curves

HGB

- Training Score: Starts quite high (around 0.96) for small training sets and gradually decreases to the low 0.90s as training size grows.
- Cross-Validation (CV) Score: Starts around 0.82–0.83 and steadily increases to about 0.88.
- The training and CV curves move closer together as more data is used, suggesting the model is generalising well.
- There maybe some overfitting at small training sizes, where the training accuracy is much higher than the CV accuracy; but this gap closes as more data is used.
- Cross-Val (Training) Score: ~0.8756m Test Accuracy: 0.8774 - negligible gap between training and test accuracy, suggesting the model is not overfitting.
- At large training size, the F1 score is very similar between the test and training set, suggesting the model is not overfitting.

MLP

- Training Score: Fluctuates but is typically quite high (often above 0.90), peaking around 0.925 before dipping slightly toward the end. Cross-Validation (CV) Score: Starts around 0.75, climbs to the low 0.80s, and then slowly edges up to around 0.825.
- There is a larger and more persistent gap (about 0.10+ difference) between training and CV accuracy throughout most of the curve, although this does reduce with more data.
- There is a lot more fluctuation in the MLP curves, suggesting it may be more sensitive to the training data.
- The MLP model is more prone to overfitting, as indicated by the larger gap between training and CV scores.
- Cross-Val (Training) Score: ~0.8265 and Test Accuracy: 0.8225 That’s only a 0.4% difference, which is very minor and suggests the model generalises well and not overfitting.
- At large training size, the F1 score is very similar between the test and training set, suggesting the model is not overfitting.

Precision Recall Curves

ROC Curves & AUC

- MLP: AUC = 0.84
- HGB: AUC = 0.89
- Area Under the ROC Curve (AUC) is a measure of how well the model separates the classes across different decision thresholds. HGB has a higher AUC, indicating better class separability.

Precision-Recall Curves & Average Precision (AP)

- MLP :AP = 0.81
- HGB :AP = 0.73
- Average Precision (AP) is a measure of the precision-recall trade-off and is representative of the area under the Precision-Recall curve. HGB has a higher AP, and stays above the blue curve (MLP) suggesting a stronger precision-recall balance.

7.1.3 Model Complexity and Efficiency

Complexity

- MLP: Being a neural network model, it can need more extensive tuning with learning rate, hidden layers, activation functions is more sensitive to hyperparameters and can be prone to overfitting.

HGB: Being a tree-based model, it is generally less sensitive to hyperparameters, more robust to outliers, and can handle imbalanced datasets effectively. It is also more memory-efficient and faster than GradientBoostingClassifier. Also much more straightforward to tune and less prone to overfitting.

Efficiency

- MLP: Training can be relatively slower for a large network or dataset, and it may require more computational resources. MLP can be regarded a black box model, making it harder to interpret the model. Inference can be fast once trained, but ultimately will depend on size.
- HGB: Training is faster and more memory-efficient, making it suitable for large datasets and real-time applications. Also easier to extract features importance and interpret the model, compared to MLP. Inference can be quicker and more efficient then MLP, as decision trees are simpler to evaluate.

7.1.4 Conclusion from Technical Perspective

- Both models generalise very well to the test set, showing very similar results to the cross-val score, with no sign of overfitting. This may have been in part due to early stopping and cross-validation.
- HGB not only has a higher overall accuracy (about 87.74% vs. 82.25%), but also better precision, recall, and F1-scores for both classes.
- The confusion matrix for HGB shows fewer mistakes in both labeling Class 0 and Class 1.

- HGB outperforms MLP in both ROC (AUC) and PR (AP) metrics, indicating better class separability and a stronger precision-recall trade-off.
- HGB's learning curves suggest it is more stable and generalises better than MLP, which shows more overfitting and sensitivity to the training data.
- HGB is more efficient and less complex than MLP, making it a better choice for large datasets and real-time applications, especially involving fraud detection using a binary classification model and where speed and accuracy are crucial. -HGB has a higher AUC and AP, indicating better class separability and a stronger precision-recall trade-off.
- Therefore, HGB is the stronger model in this comparison.

7.2 Business Perspective

The buisness perspective requirements:

- Find the average of all claims and calculate the gross profit for the company, assuming it is double the claims; this will require an annual profit calculation based on claims made for a fraction within the year
- Assuming 10% of customers base make claims, calculate the number of customers.
- Based on the pricing model, calculate the error cost of the models and the potential savings from the model.

7.2.1 Gross Profit Calculation

```
# calculate the total claim amount

property_claim = df_pivot['AmountOfPropertyClaim'].sum()
print(f'total property claim {property_claim}')

injury_claim = df_pivot['AmountOfInjuryClaim'].sum()
print(f'total injury claim {injury_claim}')

vehicle_claim = df_pivot['AmountOfVehicleDamage'].sum()
print(f'total vehicl claim {vehicle_claim}')

total_claim = property_claim + injury_claim + vehicle_claim
print(f'total claim {total_claim}')


total property claim 210037681
total injury claim 211573147
total vehicl claim 1086746063
total claim 1508356891

# find highest and lowest dateofincident
print(df_pivot['DateOfIncident'].min())
print(df_pivot['DateOfIncident'].max())

2015-01-01 00:00:00
2015-03-14 00:00:00
```

```
#calculate number of days between the highest and lowest date of
incident
from datetime import datetime
date_format = "%Y-%m-%d"
a = datetime.strptime('2015-01-01', date_format)
b = datetime.strptime('2015-03-14', date_format)
delta = b - a
print(f'total number of days covered by data {delta.days}')
```

```
total number of days covered by data 72
```

```
#number of claims
print(f'number of claims {df_pivot['Unique_ID'].count()}')
```

```
number of claims 28836
```

```
#average number of incidents per day
print(f' average number of incidents per day
{df_pivot['Unique_ID'].count()/delta.days}')

#average claim amount per day
print(f' average claim amount per day {total_claim/delta.days}')
```

```
 average number of incidents per day 400.5
 average claim amount per day 20949401.263888888
```

```
#estimated annual claim cost
estimated_annual_claim_cost = total_claim/delta.days * 365
print(f'estimated annual claim cost:
{estimated_annual_claim_cost:.2f}')

company_profit_needed = estimated_annual_claim_cost * 2
print(company_profit_needed)
print(f"Company Profit_needed: {company_profit_needed:.2f}")
```

```
estimated annual claim cost: 7646531461.32
15293062922.638887
Company Profit_needed: 15293062922.64
```

Presumabilty this figure is in Indian rupees given all the incidents are in India.

7.2.2 Number of Customers

```
no_customers = df_pivot['Unique_ID'].count() * 10
print(f'no of customers: {no_customers.round()}')

# charge for each customer
```

```
premium_per_customer = company_profit_needed/no_customers
print(f'premium per customer: Indian rupees ₹
{charge_per_customer:.2f}')
```

```
no of customers: 288360
premium per customer: Indian rupees ₹ 53034.62
```

₹ 53034.62 amounts to £499.42 per customer, for an insurance policy which sound reasonable.

7.2.3 Error Cost Calculation

```
total_claim_amount = total_claim
num_claims = df_pivot['Unique_ID'].count()


# Model performance metrics (confusion matrix values)
fn_mlp = 574  # False negatives for MLP
fp_mlp = 450  # False positives for MLP

fn_gb = 474  # False negatives for Gradient Boosting
fp_gb = 233  # False positives for Gradient Boosting

# for annual error calculation
fn_mlp_annual = (fn_mlp / delta.days)*365
fp_mlp_annual = (fp_mlp / delta.days)*365

fn_gb_annual = (fn_gb / delta.days)*365
fp_gb_annual = (fp_gb / delta.days)*365

# Average Claim Amount per day
average_claim = total_claim_amount / num_claims #over 73 days
print("Average Claim Amount:", average_claim)

#Average Claim Amount per anum
average_claim_annum = average_claim * 365

# Step 2: Calculate Total Customers
total_customers = no_customers
print("Total Customers:", total_customers)

# Step 3: Calculate Premium Per Customer

print("Premium Per Customer:", premium_per_customer)

# Step 4: Calculate Losses for MLP
fn_loss_mlp = fn_mlp_annual * average_claim_annum # False negatives
fp_loss_mlp = fp_mlp_annual * 2 * average_claim_annum # False
positives
total_loss_mlp = fn_loss_mlp + fp_loss_mlp # Total loss
```

```
print("\nMLP Losses:")
print("FN Loss:", fn_loss_mlp)
print("FP Loss:", fp_loss_mlp)
print("Total Loss:", total_loss_mlp)

# Step 5: Calculate Losses for Gradient Boosting
fn_loss_gb = fn_gb_annual * average_claim_annum
fp_loss_gb = fp_gb_annual * 2 * average_claim_annum
total_loss_gb = fn_loss_gb + fp_loss_gb

print("\nGradient Boosting Losses:")
print("FN Loss:", fn_loss_gb)
print("FP Loss:", fp_loss_gb)
print("Total Loss:", total_loss_gb)
```

```
Average Claim Amount: 52308.11801220696
Total Customers: 288360
Premium Per Customer: 53034.61965126539

MLP Losses:
FN Loss: 55556415815.68307
FP Loss: 87109362777.2034
Total Loss: 142665778592.88647

Gradient Boosting Losses:
FN Loss: 45877597729.327126
FP Loss: 45103292282.418655
Total Loss: 90980890011.74579
```

In summary:

Overall Loss Comparison:

- MLP: ₹ 142.66B total loss
- HGB: ₹ 90.98B total loss

MLP

- FN Loss: 55.56B
- FP Loss: 87.11B

HGB

- FN Loss: 45.88B
- FP Loss: 45.10B

HGB losses are balanced where as MLP has a higher loss from false positives, suggesting it is overestimating the number of fraudulent claims. Most importantly, the FN, which is the most critical error in fraud detection, is lower in HGB, suggesting it is better at identifying fraudulent claims.

HGB is significantly more cost-effective than MLP, with a potential saving of ₹ 51.68B; due to HGB's better performance in correctly identifying fraudulent claims, leading to fewer false negatives and more savings for the company.

7.3.4 Potential Savings and Loss from the Models

```
#If HGB chosen over MLP

Savings_from_HGB = total_loss_mlp - total_loss_gb
print(f"Savings from HGB over MLP: ₹ {Savings_from_HGB:.2f}")

Savings from HGB over MLP: ₹ 51684888581.14

# How much HGB can cost the company due to false negatives

loss_from_HGB = fn_loss_gb
print(f"Loss from HGB due to False Negatives: ₹ {loss_from_HGB:.2f}")

Loss from HGB due to False Negatives: ₹ 45877597729.33

 #Model performance metrics (confusion matrix values)
tp_mlp = 983  # True positive for MLP
tn_mlp = 3761  # True negative  for MLP

tn_gb = 3978 # True negatives for Gradient Boosting
tp_gb = 983  # True positives for Gradient Boosting

# for annual error calculation
tn_mlp_annual = (tn_mlp / delta.days)*365
tp_mlp_annual = (tp_mlp / delta.days)*365

tn_gb_annual = (tn_gb / delta.days)*365
tp_gb_annual = (tp_gb / delta.days)*365


#Calculate Gains  for Gradient Boosting
tn_gain_gb = tn_gb_annual * average_claim_annum # True negatives
tp_gain_gb = tp_gb_annual * 2 * average_claim_annum # True positives
total_gain_gb = tn_gain_gb + tp_gain_gb # Total gain



print("\nGradient Boosting Positives:")
print("TN Positive:", tn_gain_gb)
print("TP Positive:", tp_gain_gb)
print("Total Positives:", total_gain_gb)


Gradient Boosting Positives:
TN Positive: 385023383475.2391
TP Positive: 190285563577.7577
Total Positives: 575308947052.9968
```

```
#How much a company can save by using HGB over no model

#by using HGB, the company can correctly identify fraudent causes

savings_due_to_HGB = tp_gain_gb #identify fraud causes
print(f"Savings due to recognising fraud claims using HGB: ₹
{savings_due_to_HGB:.2f}")

total_savings = savings_due_to_HGB - loss_from_HGB #total savings
print(f"Total Savings using HGB: ₹ {total_savings:.2f}")

Savings due to recognising fraud claims using HGB: ₹ 190285563577.76
Total Savings using HGB: ₹ 144407965848.43
```

7.3.5 Conclusion from Business Perspective

- The company will save ₹ 144.4BN by using HGB; this includes loss due to false negatives and gains due to true positives.

- HGB is more cost-effective than MLP, with a potential saving of ₹ 51.68B over MLP due to HGB's better performance in correctly identifying fraudulent claims, leading to fewer false negatives and more savings for the company.

7.3 Overall Recommendation

HistGradientBoostingClassifier is recommended over MLPClassifier for the following reasons:

- HGB has a higher overall accuracy, precision, recall, and F1-scores for both classes.
- HGB shows fewer mistakes in both labeling Class 0 and Class 1.
- HGB outperforms MLP in both ROC (AUC) and PR (AP) metrics, indicating better class separability and a stronger precision-recall trade-off.
- HGB’s learning curves suggest it is more stable and generalises better than MLP, which shows more overfitting and sensitivity to the training data.
- HGB is more efficient and less complex than MLP, making it a better choice for large datasets and real-time applications, especially involving fraud detection using a binary classification model and where speed and accuracy are crucial.
- HGB is significantly more cost-effective than MLP, with a potential saving of ₹ 51.68B over MLP due to HGB's better performance in correctly identifying fraudulent claims, leading to fewer false negatives and more savings for the company.

Therefore, HGB is the stronger model in this comparison and is recommended for fraud detection in the insurance company.

8. Conclusion

8.1 What has been successfully accomplished and what has not

After weeks of non-stop work, I have successfully pre-processeed the data, built two models, and evaluated them using nested cross-validation. I have also compared the models from both technical and business perspectives. The HistGradientBoostingClassifier model outperformed the MLPClassifier in terms of accuracy, precision, recall, F1-scores, and cost-effectiveness. The HGB model is more stable, generalises better, and is more efficient than the MLP model. It is also more cost-effective, with a potential saving of ₹ 51.68B over MLP due to its better performance in correctly identifying fraudulent claims.

The aims and objectives in the project brief have been met, and the final recommendation is to use the HGB model for fraud detection in the insurance company.

What hasn't been accomplished is the unbiased predictive model having a balanced error of 5% or less.

8.2 Reflect back on the analysis and see what you could have done differently if you were to do the project again

- Balancing the weights was tricky using MLP, as the library didnt have built-in handling for class imbalance; this took significant time to resolve. In hinsight, I could have used a different model that has built-in handling for class imbalance.
- I could have used a different feature selection method, such as PCA, to see if it would have improved the model's performance.
- I also underestimated the time it would take to resolve technical issues throughout the model buiilding and nested cross-validation process. I could have allocated more time for this. I had to use RandomizedSearchCV instead of GridSearchCV for the MLP model due to the time constraints as GridSearchCV was taking too long to run.

8.3 Add a wish list of future work that you would do to take the project forward

As future work, I would be interested in exploring the following:

- How Bayesian optimization could be used to tune the hyperparameters of the models more efficiently; also how this compares to GridSearchCV and RandomizedSearchCV.
- If there is scope for unsupervised learning techniques, such as anomaly detection, to identify fraudulent claims without the need for labels.
- How ensemble methods, such as stacking, could be used to combine the predictions of multiple models to improve the overall performance.
- Find models that have a lower error rate, approximating the 5% error rate target set in the project brief.

9. References

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