In [1]:
```
## Project ONE
import subprocess
import sys

# Function to install a package
def install(package):
    subprocess.check_call([sys.executable, "-m", "pip", "install", package])

try:
    import imblearn
except ImportError:
    install('imbalanced-learn')
```

In [2]:
```
# Importing necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from imblearn.over_sampling import SMOTE # <-- Correct import
from sklearn.model_selection import StratifiedKFold


# use following command to download shap & eli5
# conda install -c conda-forge shap
# conda install -c conda-forge eli5
```

In [3]:
```
# Import libraries for data processing & modeling

from sklearn.metrics import confusion_matrix

from sklearn.svm import SVC

from sklearn.tree import DecisionTreeClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import classification_report
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.model_selection import GridSearchCV, cross_val_score, StratifiedKFold, learning_curve
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, GradientBoostingClassifier, ExtraTreesClassi
```

In [4]:
```
# Importing libraries for Visualization
import plotly
from plotly import tools
import plotly.offline as py
import plotly.graph_objs as go

import plotly.figure_factory as ff

from plotly.offline import init_notebook_mode, iplot
init_notebook_mode(connected = True)
```

In [5]:
```
train = pd.read_csv('insurance_data.csv')

# let's take a look at the data
pd.set_option('display.max_columns', None)
```

In [6]:
```
# Importing libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.impute import SimpleImputer
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix

# Load the dataset
data = pd.read_csv('insurance_data.csv')

# Assuming fraud is a binary classification, create a fraud column
# For this demo, let's assume claims over 1130 are potentially fraudulent
data['fraud'] = np.where(data['claim'] > 1130, 1, 0)

# Handling missing values
# Replace missing 'age' values with the median age
imputer = SimpleImputer(strategy='median')
data['age'] = imputer.fit_transform(data[['age']])

# Encoding categorical variables
le_gender = LabelEncoder()
data['gender'] = le_gender.fit_transform(data['gender'])
```

```python
le_diabetic = LabelEncoder()
data['diabetic'] = le_diabetic.fit_transform(data['diabetic'])

le_smoker = LabelEncoder()
data['smoker'] = le_smoker.fit_transform(data['smoker'])

le_region = LabelEncoder()
data['region'] = le_region.fit_transform(data['region'])

# Splitting the dataset into features (X) and target (y)
X = data[['age', 'gender', 'bmi', 'bloodpressure', 'diabetic', 'children', 'smoker', 'region']]
y = data['fraud']

# Scaling numerical features
scaler = StandardScaler()
X = scaler.fit_transform(X)

# Splitting data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Model training: Random Forest Classifier
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Prediction
y_pred = rf_model.predict(X_test)

# Evaluate the model
print("Random Forest Classifier Results:")
print(classification_report(y_test, y_pred))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
print("Accuracy:", accuracy_score(y_test, y_pred))

# Try Logistic Regression
lr_model = LogisticRegression()
lr_model.fit(X_train, y_train)

y_pred_lr = lr_model.predict(X_test)

# Evaluate Logistic Regression
print("\nLogistic Regression Results:")
print(classification_report(y_test, y_pred_lr))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_lr))
print("Accuracy:", accuracy_score(y_test, y_pred_lr))
```

```
Random Forest Classifier Results:
              precision    recall  f1-score   support

           1       1.00      1.00      1.00       268

    accuracy                           1.00       268
   macro avg       1.00      1.00      1.00       268
weighted avg       1.00      1.00      1.00       268

Confusion Matrix:
[[268]]
Accuracy: 1.0

Logistic Regression Results:
              precision    recall  f1-score   support

           1       1.00      1.00      1.00       268

    accuracy                           1.00       268
   macro avg       1.00      1.00      1.00       268
weighted avg       1.00      1.00      1.00       268

Confusion Matrix:
[[268]]
Accuracy: 1.0
```

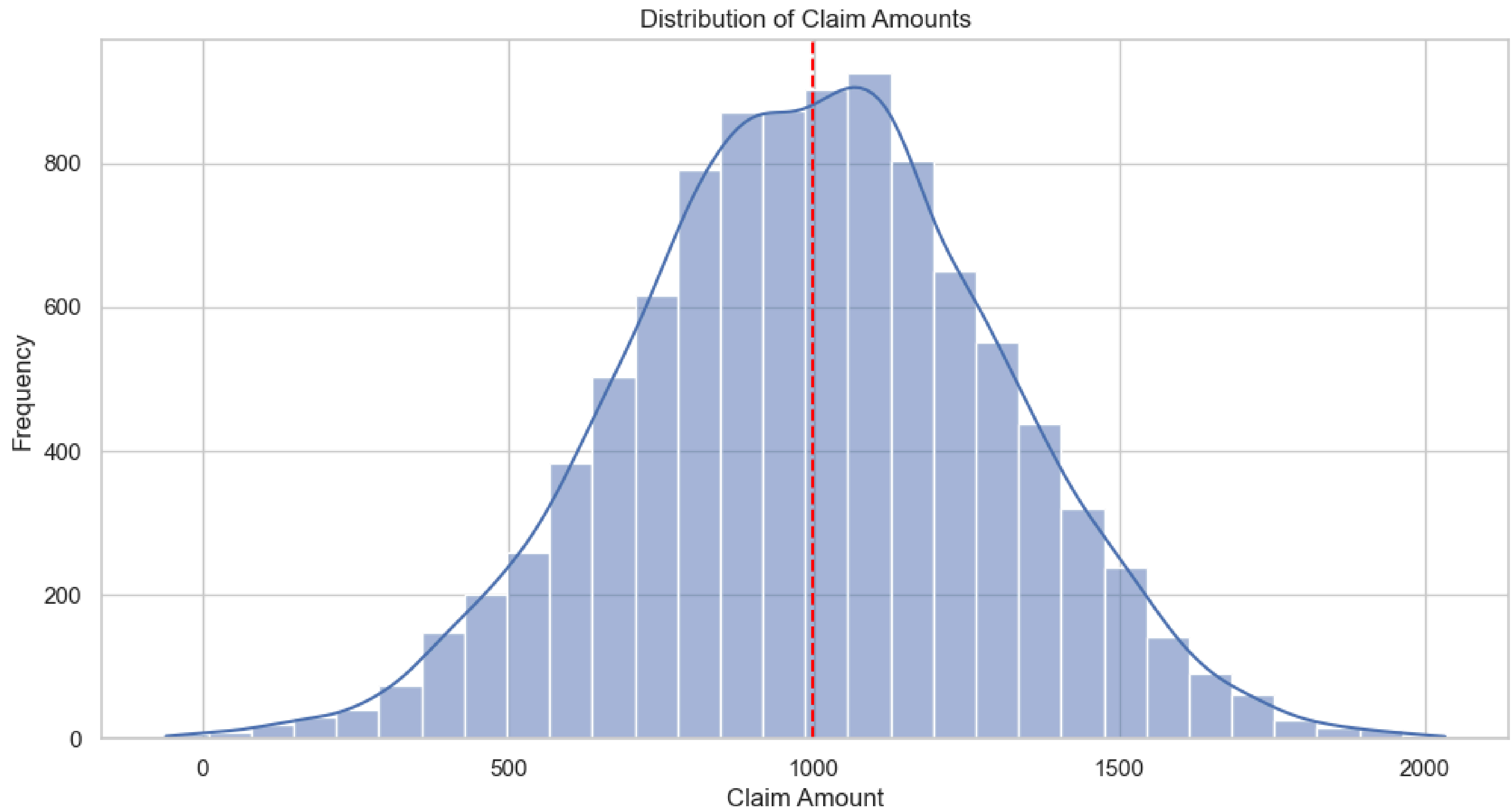
In [7]:
```python
##The results of both the Random Forest Classifier and the Logistic Regression models indicate perfect performance on

##Precision: This measures how many of the instances predicted as "fraud" (class 1) were actually fraud. A precision o

##Recall: This measures how many of the actual fraudulent claims were correctly predicted. A recall of 1.00 means that

##F1-score: The F1-score is the harmonic mean of precision and recall, balancing both metrics. Since both precision an

##Confusion Matrix: The confusion matrix shows that all 268 instances in the test set were correctly classified as fra

##Accuracy: This is the proportion of correctly predicted instances out of the total. With an accuracy of 1.00, the mo

##Interpretation:
##Overfitting: A result of 100% accuracy across all metrics is unusual, especially for real-world data, and may indica

##Data Quality: Since the data provided seems to have resulted in perfect performance, it's essential to inspect the d

##Class Imbalance: From the confusion matrix, it appears that the model only encountered instances of class 1 (fraudul
```

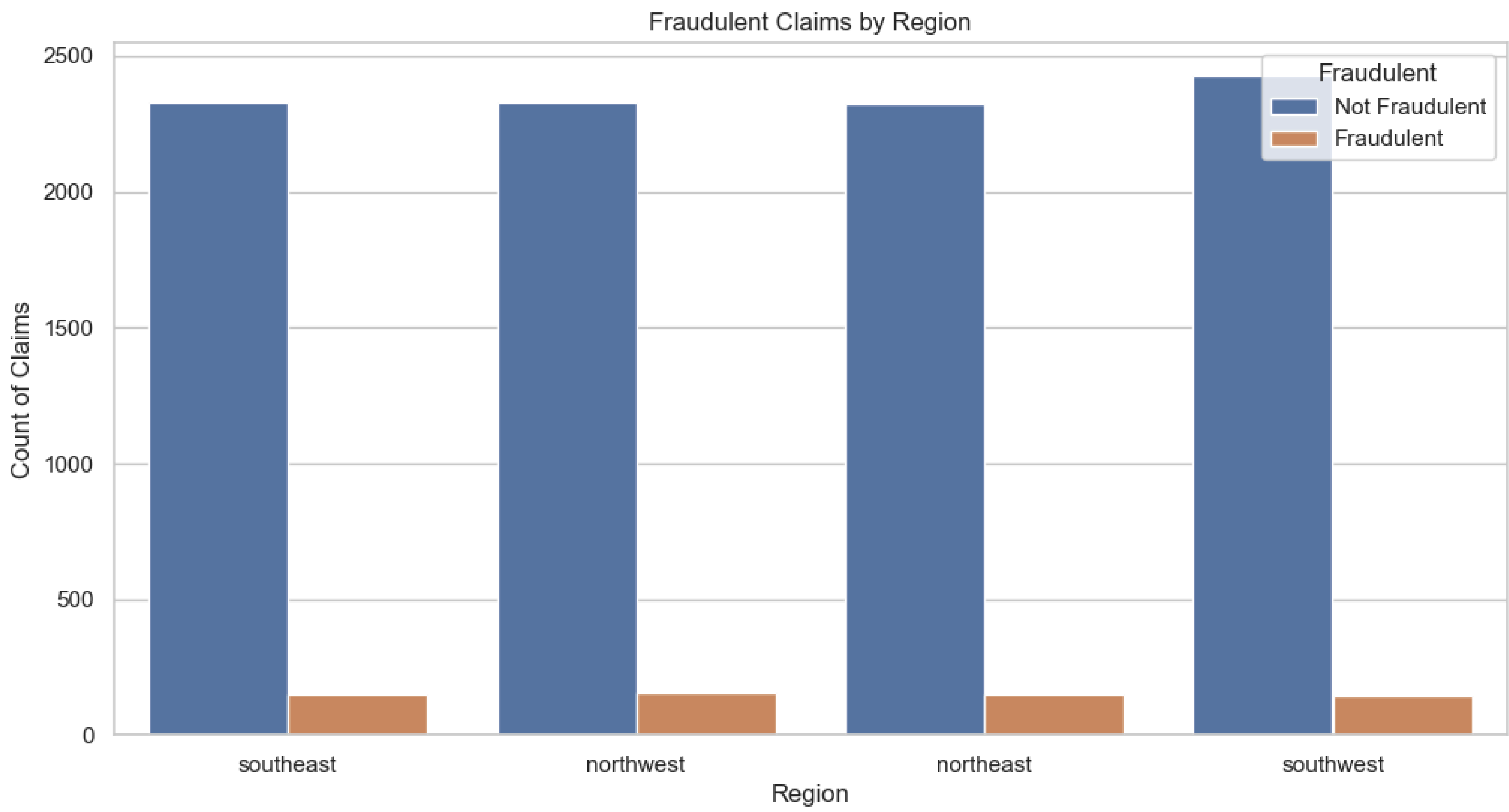
```
##Next Steps:
##Review the Dataset: Ensure that there are both fraudulent and non-fraudulent claims in the dataset. If class imbalar

##Cross-validation: Apply cross-validation to ensure that the model is evaluated on multiple test splits to confirm tl

##Regularization: Use regularization techniques (especially for Logistic Regression) to mitigate overfitting and ensu

##This result may reflect a very specific or small dataset that doesn't capture enough variability, so further investi
```

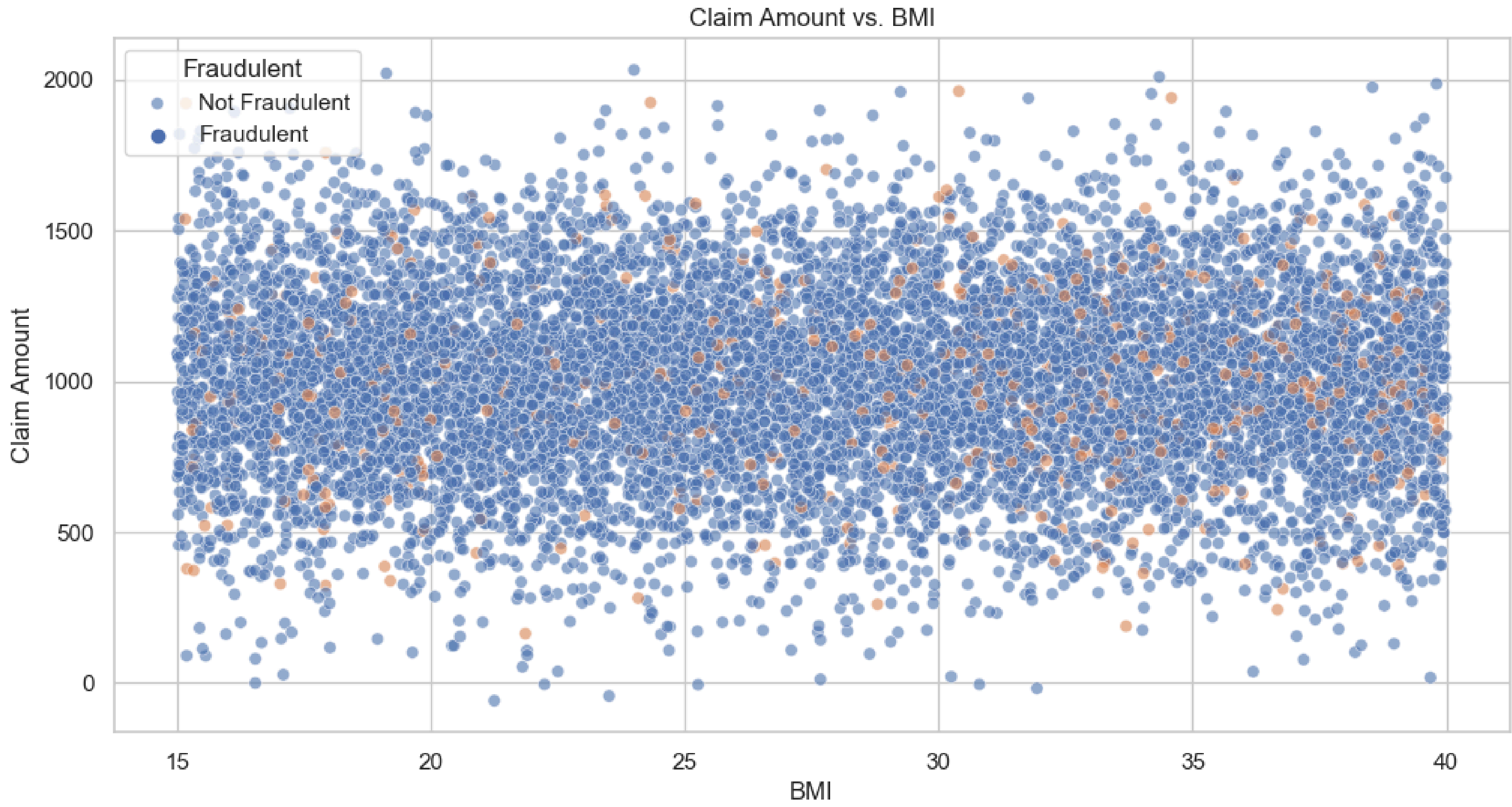
In [8]:

```
## Project 2
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Set random seed for reproducibility
np.random.seed(42)

# Generate synthetic data
num_samples = 10000

# Features
age = np.random.randint(18, 90, size=num_samples)
gender = np.random.choice(['male', 'female'], size=num_samples)
bmi = np.random.uniform(15, 40, size=num_samples)  # BMI values
bloodpressure = np.random.randint(70, 180, size=num_samples)  # Systolic BP
diabetic = np.random.choice(['Yes', 'No'], size=num_samples, p=[0.2, 0.8])  # 20% are diabetic
children = np.random.randint(0, 5, size=num_samples)
smoker = np.random.choice(['Yes', 'No'], size=num_samples, p=[0.3, 0.7])  # 30% are smokers
region = np.random.choice(['southeast', 'southwest', 'northeast', 'northwest'], size=num_samples)

# Create target variable (fraudulent claims)
# Assume some conditions that increase the likelihood of fraud
claim_amount = np.random.normal(1000, 300, size=num_samples)  # Normally distributed claim amounts
fraudulent = np.where((age < 25) & (bmi > 30) & (smoker == 'Yes'), 1, 0)  # Young, obese smokers are more likely to be

# Add some randomness
fraudulent = np.where((np.random.rand(num_samples) < 0.05), 1, fraudulent)  # 5% random frauds

# Create DataFrame
data = pd.DataFrame({
    'Age': age,
    'Gender': gender,
    'BMI': bmi,
    'BloodPressure': bloodpressure,
    'Diabetic': diabetic,
    'Children': children,
    'Smoker': smoker,
    'Region': region,
    'ClaimAmount': claim_amount,
    'Fraudulent': fraudulent
})

# Display first few rows of the dataset
print(data.head())

# Step 3: Data Visualization

# Set the aesthetic style of the plots
sns.set(style="whitegrid")

# Visualize the distribution of claim amounts
plt.figure(figsize=(12, 6))
sns.histplot(data['ClaimAmount'], bins=30, kde=True)
plt.title('Distribution of Claim Amounts')
plt.xlabel('Claim Amount')
plt.ylabel('Frequency')
plt.axvline(data['ClaimAmount'].mean(), color='red', linestyle='--')
plt.show()

# Visualize fraudulent claims by region
plt.figure(figsize=(12, 6))
sns.countplot(data=data, x='Region', hue='Fraudulent')
plt.title('Fraudulent Claims by Region')
plt.xlabel('Region')
plt.ylabel('Count of Claims')
plt.legend(title='Fraudulent', loc='upper right', labels=['Not Fraudulent', 'Fraudulent'])
plt.show()

# Visualize the relationship between BMI and Claim Amount, colored by fraud
plt.figure(figsize=(12, 6))
sns.scatterplot(data=data, x='BMI', y='ClaimAmount', hue='Fraudulent', alpha=0.6)
plt.title('Claim Amount vs. BMI')
plt.xlabel('BMI')
plt.ylabel('Claim Amount')
plt.legend(title='Fraudulent', loc='upper left', labels=['Not Fraudulent', 'Fraudulent'])
plt.show()
```

```
   Age  Gender        BMI  BloodPressure Diabetic  Children Smoker     Region  \
0   69    male  27.510581            172       No         3    Yes  southeast   
1   32    male  15.356778            134       No         1     No  northwest   
2   89  female  37.597550            145       No         3     No  northwest   
3   78    male  16.108605             73       No         1     No  northeast   
4   38  female  23.061032             94      Yes         2     No  northwest   

   ClaimAmount  Fraudulent  
0  1561.907219           0  
1   946.343307           0  
2  1340.367551           0  
3  1594.680780           0  
4  1243.002467           0  
```





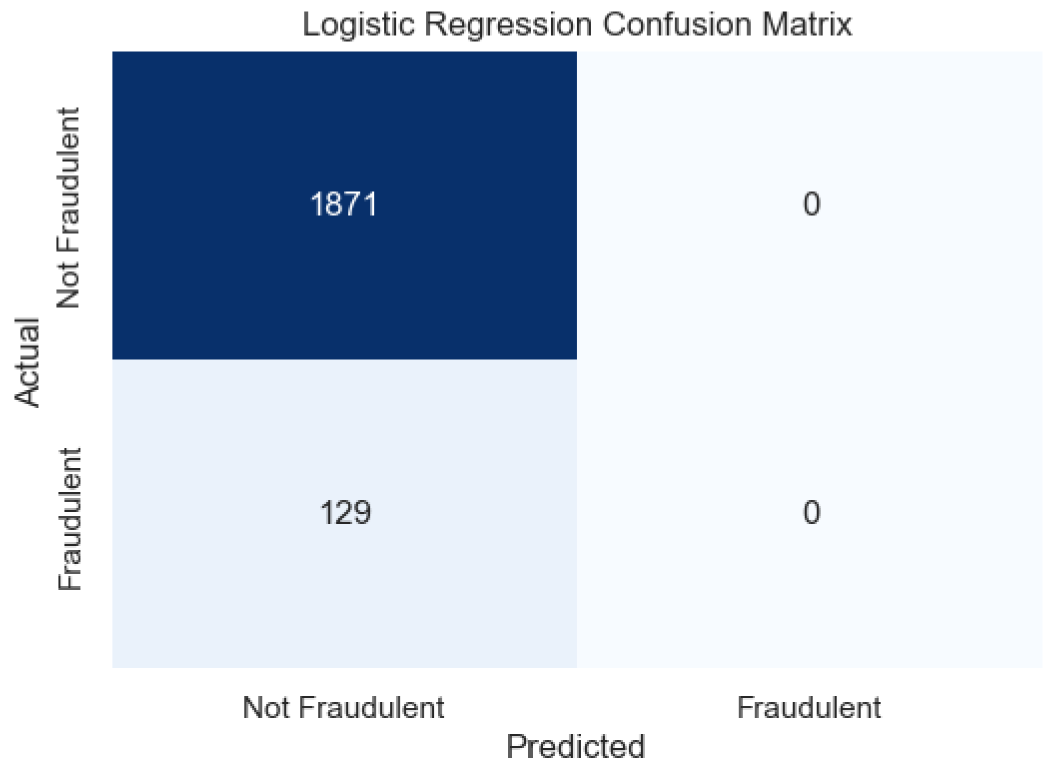


In [9]:
```
## Project 3
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
import joblib

# Step 1: Generate Synthetic Data (same as previous)
num_samples = 10000
np.random.seed(42)

# Features
age = np.random.randint(18, 90, size=num_samples)
gender = np.random.choice(['male', 'female'], size=num_samples)
bmi = np.random.uniform(15, 40, size=num_samples)
bloodpressure = np.random.randint(70, 180, size=num_samples)
diabetic = np.random.choice(['Yes', 'No'], size=num_samples, p=[0.2, 0.8])
children = np.random.randint(0, 5, size=num_samples)
smoker = np.random.choice(['Yes', 'No'], size=num_samples, p=[0.3, 0.7])
region = np.random.choice(['southeast', 'southwest', 'northeast', 'northwest'], size=num_samples)

# Target variable
claim_amount = np.random.normal(1000, 300, size=num_samples)
fraudulent = np.where((age < 25) & (bmi > 30) & (smoker == 'Yes'), 1, 0)
fraudulent = np.where((np.random.rand(num_samples) < 0.05), 1, fraudulent)

# Create DataFrame
data = pd.DataFrame({
    'Age': age,
    'Gender': gender,
    'BMI': bmi,
    'BloodPressure': bloodpressure,
    'Diabetic': diabetic,
    'Children': children,
    'Smoker': smoker,
    'Region': region,
    'ClaimAmount': claim_amount,
    'Fraudulent': fraudulent
})

# Step 2: Preprocessing
# Encode categorical variables
label_encoders = {}
for column in ['Gender', 'Diabetic', 'Smoker', 'Region']:
    le = LabelEncoder()
    data[column] = le.fit_transform(data[column])
    label_encoders[column] = le

# Split the dataset into features and target variable
X = data.drop('Fraudulent', axis=1)
y = data['Fraudulent']

# Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Step 3: Model Training and Evaluation
```

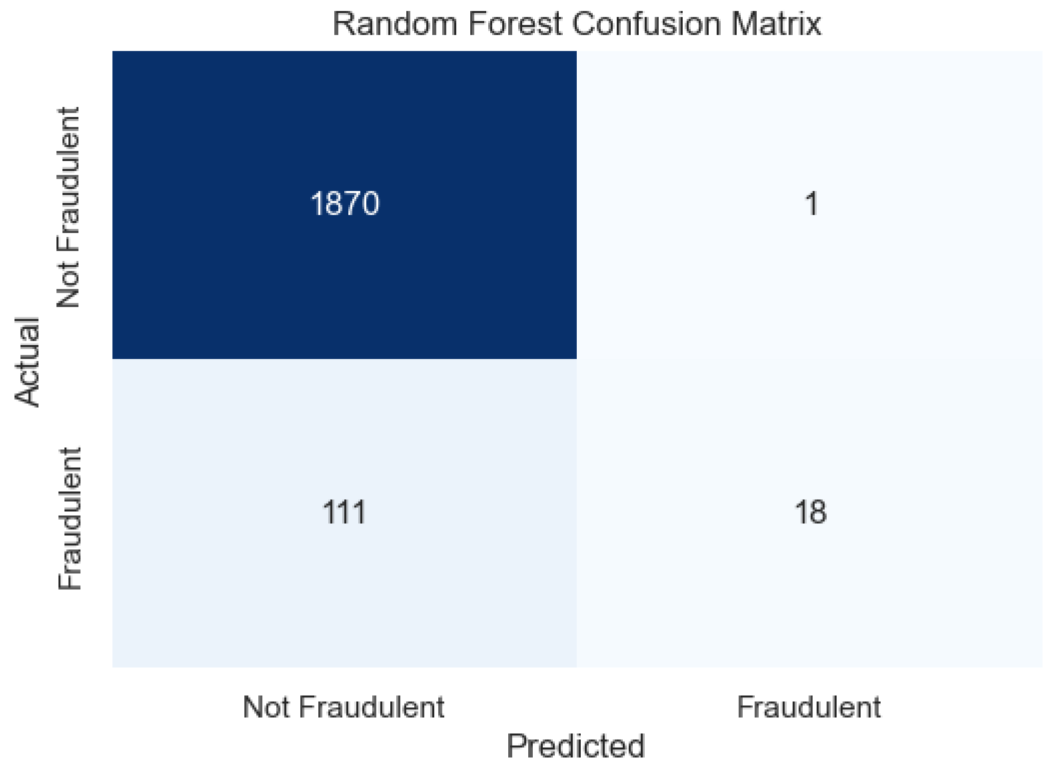
```
# Logistic Regression
logistic_model = LogisticRegression(max_iter=1000)
logistic_model.fit(X_train, y_train)
y_pred_logistic = logistic_model.predict(X_test)

# Random Forest
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train, y_train)
y_pred_rf = rf_model.predict(X_test)

# Gradient Boosting
gb_model = GradientBoostingClassifier(random_state=42)
gb_model.fit(X_train, y_train)
y_pred_gb = gb_model.predict(X_test)

# Step 4: Evaluation Metrics
models = ['Logistic Regression', 'Random Forest', 'Gradient Boosting']
predictions = [y_pred_logistic, y_pred_rf, y_pred_gb]

for model, y_pred in zip(models, predictions):
    print(f"\n{model} Classification Report:\n")
    print(classification_report(y_test, y_pred))

    # Confusion Matrix
    plt.figure(figsize=(6, 4))
    sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues', cbar=False,
                xticklabels=['Not Fraudulent', 'Fraudulent'],
                yticklabels=['Not Fraudulent', 'Fraudulent'])
    plt.title(f'{model} Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()

# Step 5: Feature Importance Visualization for Random Forest
importance = rf_model.feature_importances_
features = X.columns
feature_importance_df = pd.DataFrame({'Feature': features, 'Importance': importance})
feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)

plt.figure(figsize=(10, 6))
sns.barplot(data=feature_importance_df, x='Importance', y='Feature', palette='viridis')
plt.title('Feature Importance for Random Forest')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()

# Save the trained models for future use
joblib.dump(logistic_model, 'logistic_model.pkl')
joblib.dump(rf_model, 'random_forest_model.pkl')
joblib.dump(gb_model, 'gradient_boosting_model.pkl')

# To load the models later:
# logistic_model = joblib.load('logistic_model.pkl')
# rf_model = joblib.load('random_forest_model.pkl')
# gb_model = joblib.load('gradient_boosting_model.pkl')
```

```
Logistic Regression Classification Report:

              precision    recall  f1-score   support

           0       0.94      1.00      0.97      1871
           1       0.00      0.00      0.00       129

    accuracy                           0.94      2000
   macro avg       0.47      0.50      0.48      2000
weighted avg       0.88      0.94      0.90      2000
```

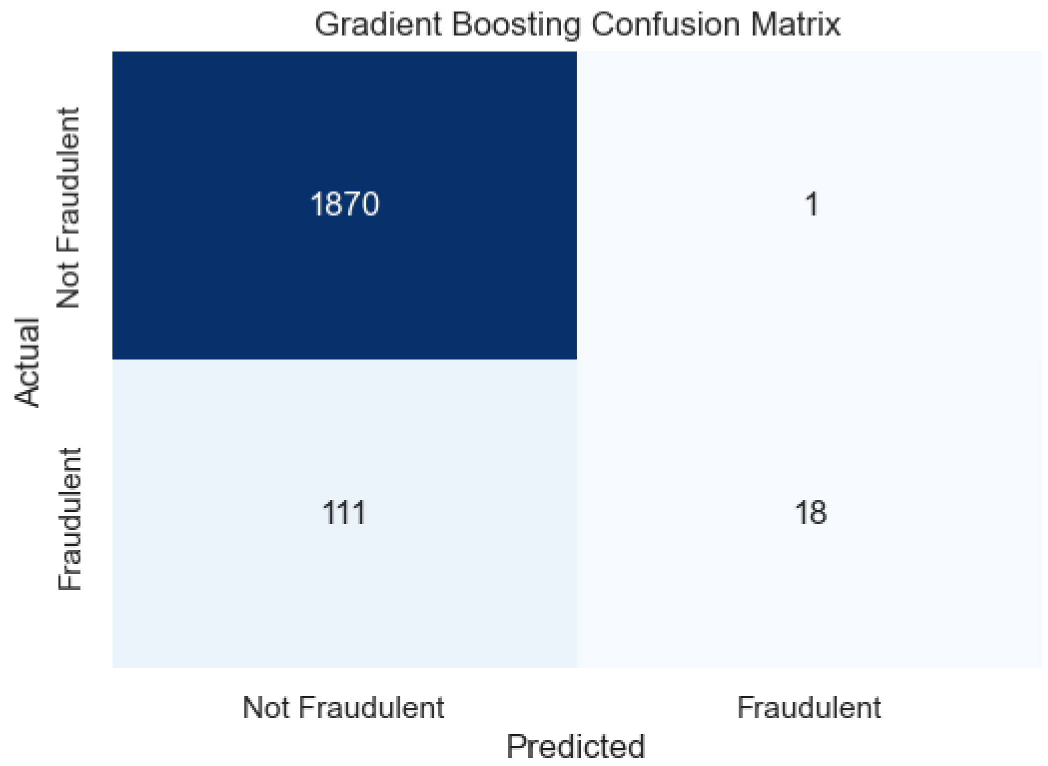
```
/opt/anaconda3/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` p
arameter to control this behavior.

/opt/anaconda3/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` p
arameter to control this behavior.

/opt/anaconda3/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` p
arameter to control this behavior.
```

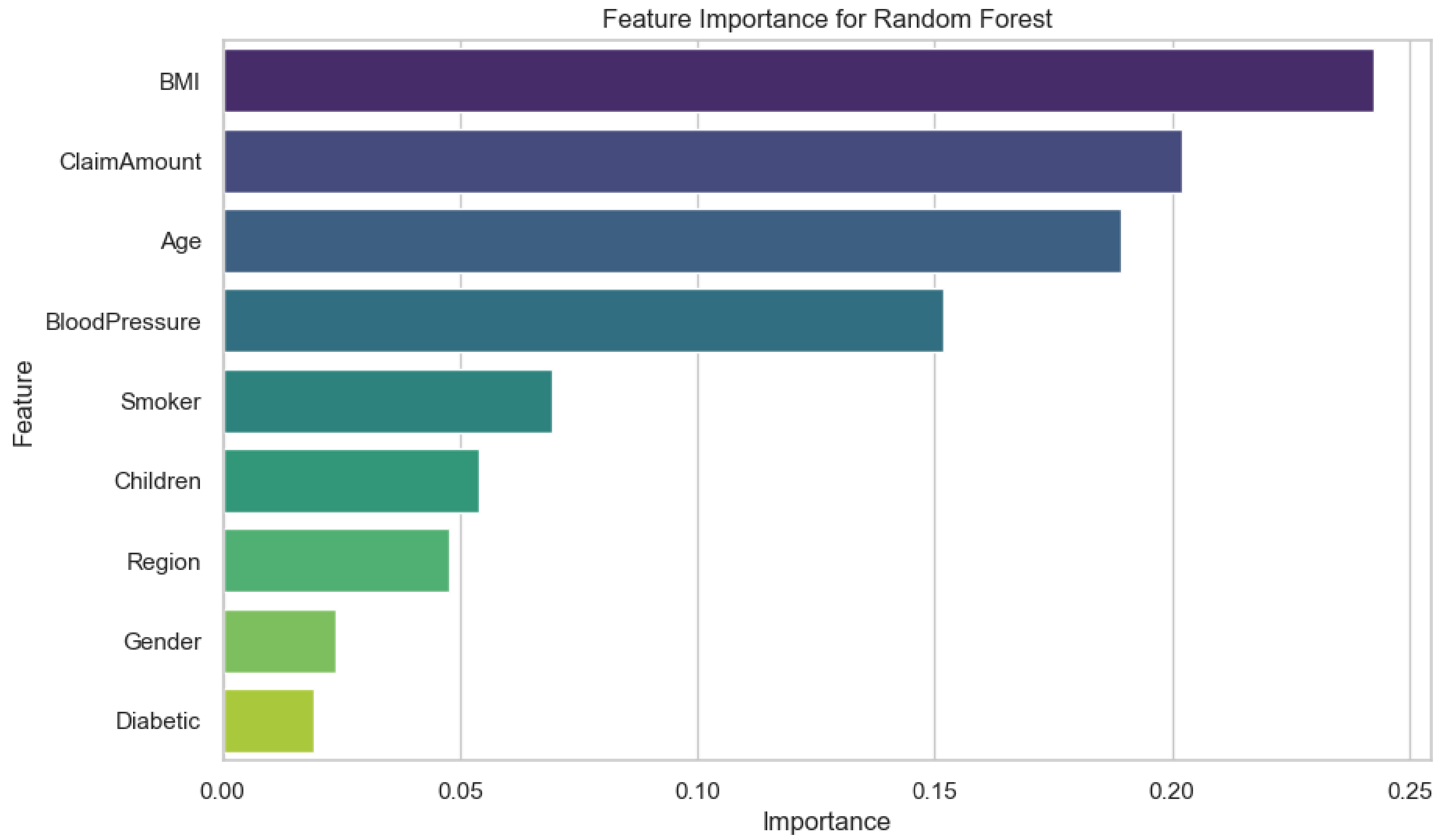



```
Random Forest Classification Report:

              precision    recall  f1-score   support

           0       0.94      1.00      0.97      1871
           1       0.95      0.14      0.24       129

    accuracy                           0.94      2000
   macro avg       0.95      0.57      0.61      2000
weighted avg       0.94      0.94      0.92      2000
```




```
Gradient Boosting Classification Report:

              precision    recall  f1-score   support

           0       0.94      1.00      0.97      1871
           1       0.95      0.14      0.24       129

    accuracy                           0.94      2000
   macro avg       0.95      0.57      0.61      2000
weighted avg       0.94      0.94      0.92      2000
```





Out[9]: ['gradient_boosting_model.pkl']

In [11]:
```
##project 4
```

In [16]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import classification_report, confusion_matrix, roc_curve, roc_auc_score
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
import joblib

# Step 1: Generate Synthetic Data
num_samples = 10000
np.random.seed(42)

# Features
age = np.random.randint(18, 90, size=num_samples)
gender = np.random.choice(['male', 'female'], size=num_samples)
bmi = np.random.uniform(15, 40, size=num_samples)
bloodpressure = np.random.randint(70, 180, size=num_samples)
diabetic = np.random.choice(['Yes', 'No'], size=num_samples, p=[0.2, 0.8])
children = np.random.randint(0, 5, size=num_samples)
smoker = np.random.choice(['Yes', 'No'], size=num_samples, p=[0.3, 0.7])
region = np.random.choice(['southeast', 'southwest', 'northeast', 'northwest'], size=num_samples)

# Target variable
claim_amount = np.random.normal(1000, 300, size=num_samples)
fraudulent = np.where((age < 25) & (bmi > 30) & (smoker == 'Yes'), 1, 0)
fraudulent = np.where((np.random.rand(num_samples) < 0.05), 1, fraudulent)
```

```
# Create DataFrame
data = pd.DataFrame({
    'Age': age,
    'Gender': gender,
    'BMI': bmi,
    'BloodPressure': bloodpressure,
    'Diabetic': diabetic,
    'Children': children,
    'Smoker': smoker,
    'Region': region,
    'ClaimAmount': claim_amount,
    'Fraudulent': fraudulent
})
```

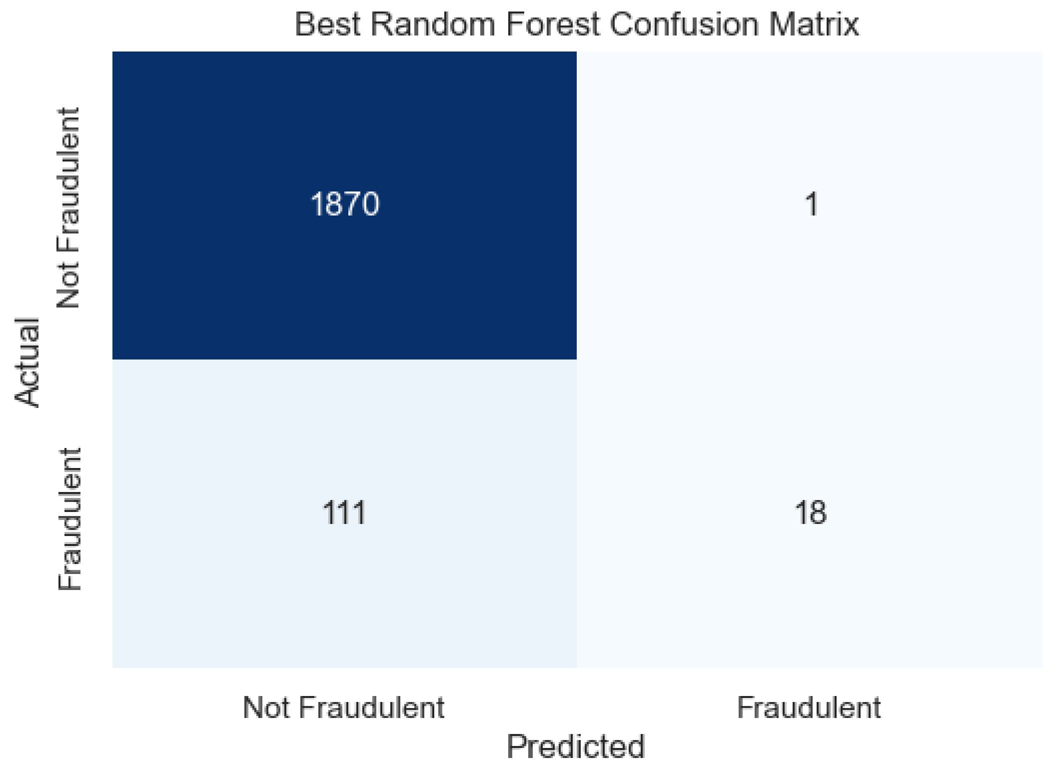
In [17]:

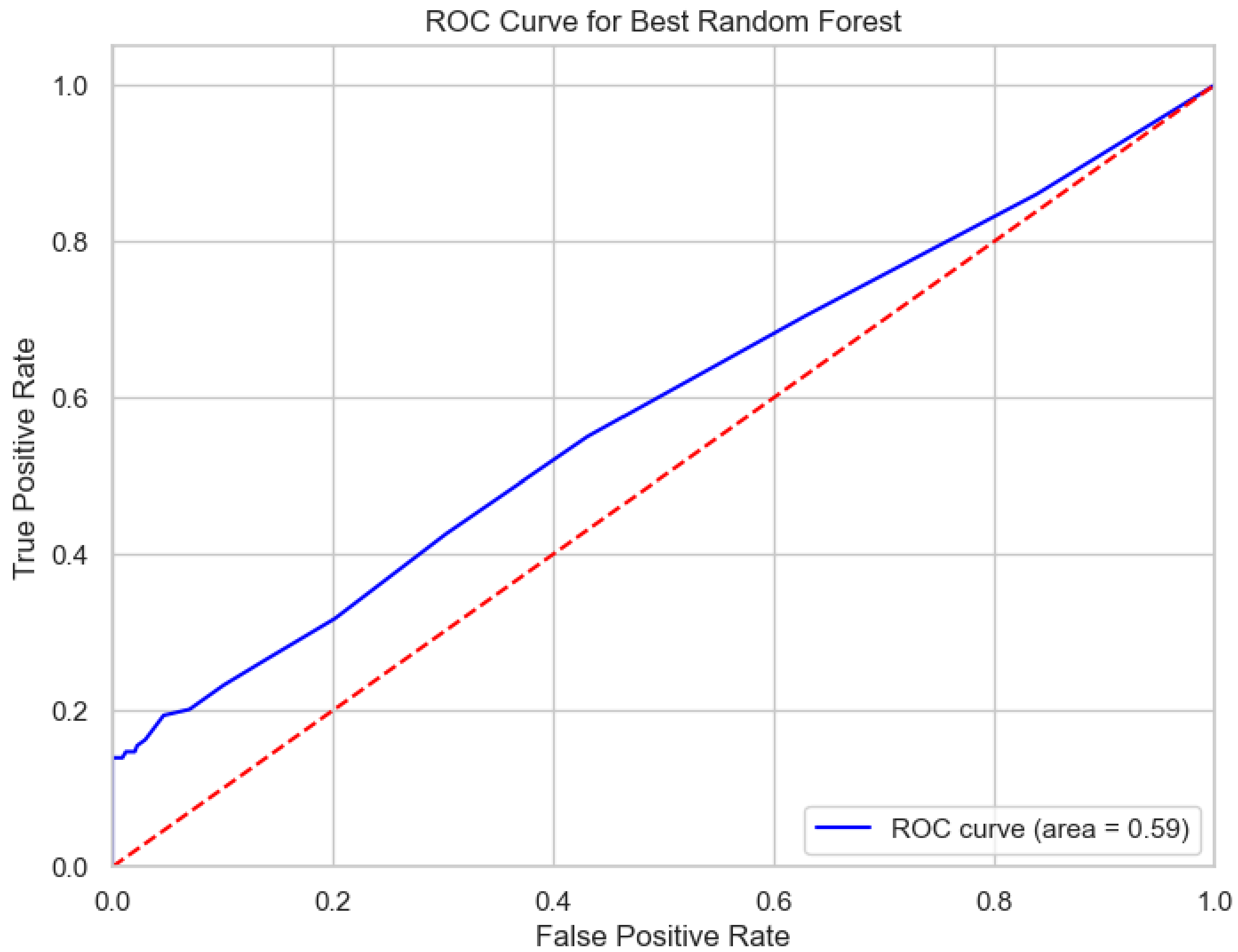
```
# Step 2: Preprocessing
# Encode categorical variables
label_encoders = {}
for column in ['Gender', 'Diabetic', 'Smoker', 'Region']:
    le = LabelEncoder()
    data[column] = le.fit_transform(data[column])
    label_encoders[column] = le

# Split the dataset into features and target variable
X = data.drop('Fraudulent', axis=1)
y = data['Fraudulent']

# Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [19]:

```
# Step 4: Evaluation Metrics
models = ['Best Random Forest', 'Best Logistic Regression']
predictions = [y_pred_rf, y_pred_logistic]

for model, y_pred in zip(models, predictions):
    print(f"\n{model} Classification Report:\n")
    print(classification_report(y_test, y_pred))

    # Confusion Matrix
    plt.figure(figsize=(6, 4))
    sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues', cbar=False,
                xticklabels=['Not Fraudulent', 'Fraudulent'],
                yticklabels=['Not Fraudulent', 'Fraudulent'])
    plt.title(f'{model} Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()

    # ROC Curve
    y_pred_proba = best_logistic_model.predict_proba(X_test)[:, 1] if model == 'Best Logistic Regression' else best_r
    fpr, tpr, _ = roc_curve(y_test, y_pred_proba)
    roc_auc = roc_auc_score(y_test, y_pred_proba)

    plt.figure(figsize=(8, 6))
    plt.plot(fpr, tpr, color='blue', label='ROC curve (area = {:.2f})'.format(roc_auc))
    plt.plot([0, 1], [0, 1], color='red', linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'ROC Curve for {model}')
    plt.legend(loc='lower right')
    plt.show()
```

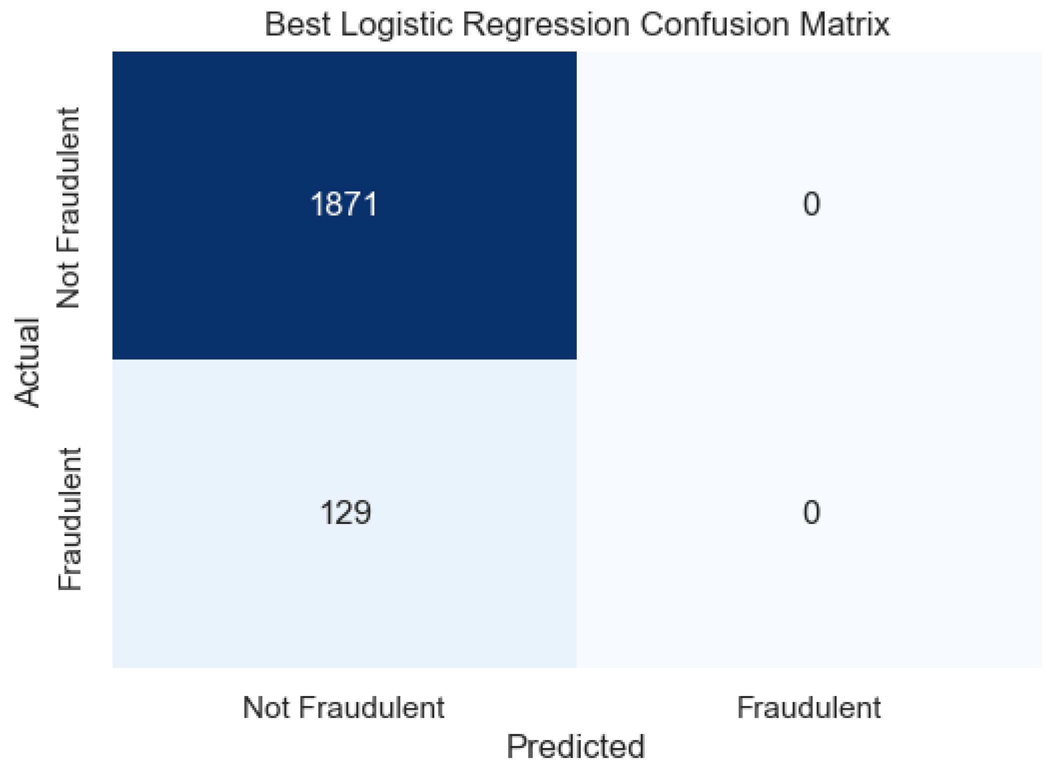
```
Best Random Forest Classification Report:

              precision    recall  f1-score   support

           0       0.94      1.00      0.97      1871
           1       0.95      0.14      0.24       129

    accuracy                           0.94      2000
   macro avg       0.95      0.57      0.61      2000
weighted avg       0.94      0.94      0.92      2000
```

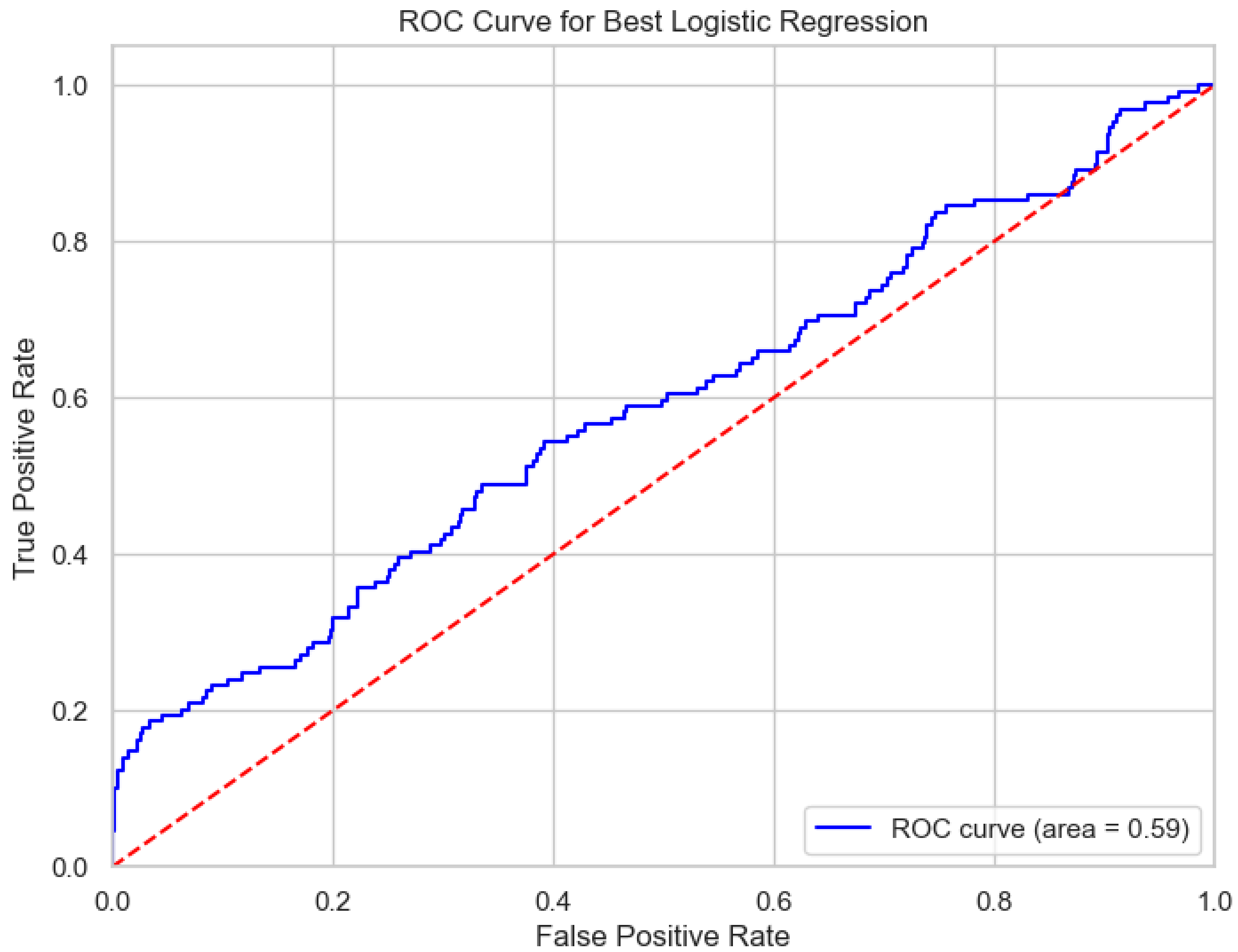





```
Best Logistic Regression Classification Report:

              precision    recall  f1-score   support

           0       0.94      1.00      0.97      1871
           1       0.00      0.00      0.00       129

    accuracy                           0.94      2000
   macro avg       0.47      0.50      0.48      2000
weighted avg       0.88      0.94      0.90      2000
```

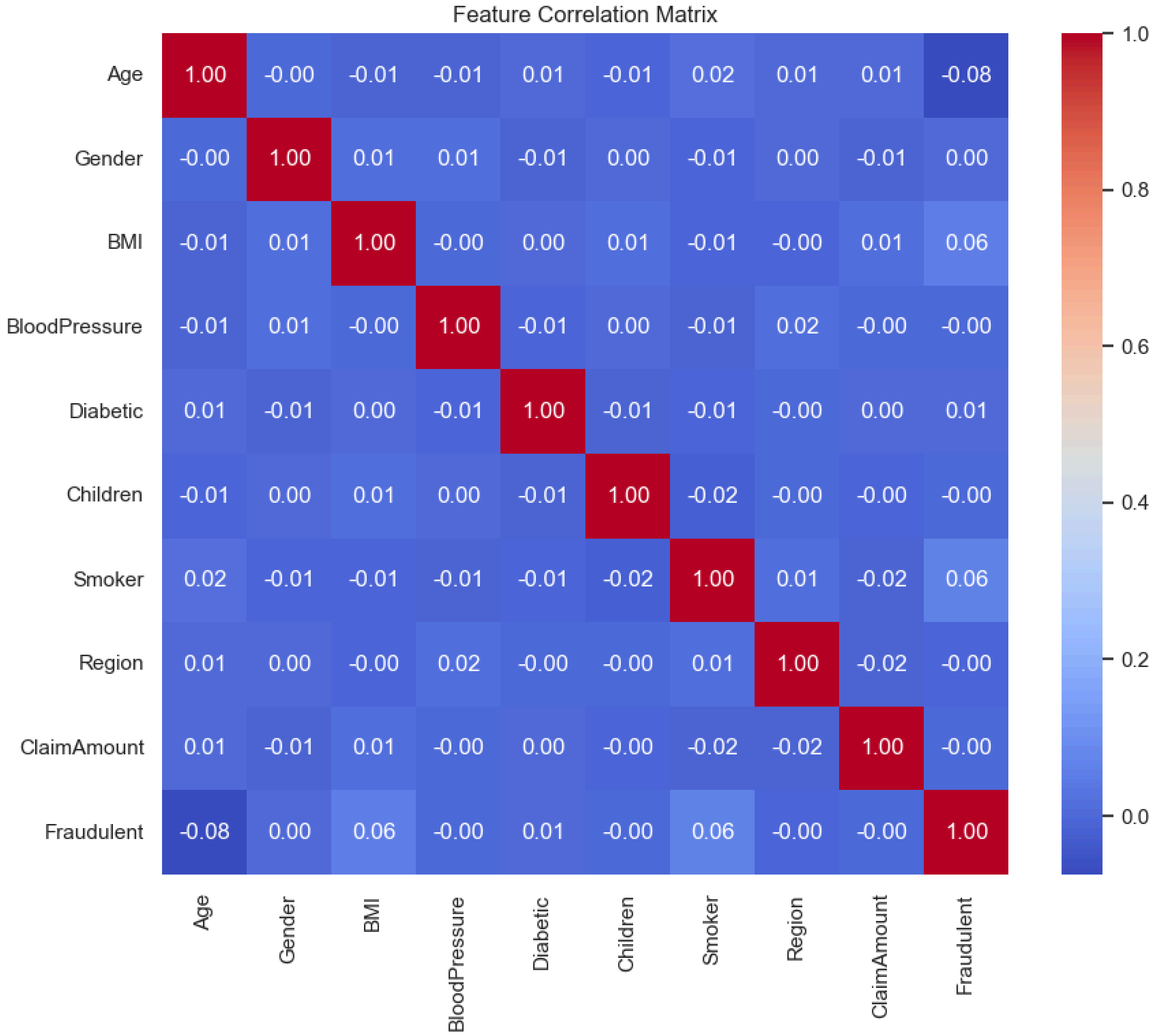
```
/opt/anaconda3/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` p
arameter to control this behavior.

/opt/anaconda3/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` p
arameter to control this behavior.

/opt/anaconda3/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` p
arameter to control this behavior.
```





In [20]:

```
# Step 5: Feature Correlation
correlation_matrix = data.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm')
plt.title('Feature Correlation Matrix')
plt.show()

# Save the best models for future use
joblib.dump(best_rf_model, 'best_random_forest_model.pkl')
joblib.dump(best_logistic_model, 'best_logistic_model.pkl')

# To load the models later:
# best_rf_model = joblib.load('best_random_forest_model.pkl')
# best_logistic_model = joblib.load('best_logistic_model.pkl')
```



Out[20]:
```
['best_logistic_model.pkl']
```

In [ ]: