Predictive Modeling for High-Income Classification Using U.S. Census Data (1994-1996)

Importing necessary packages

1.1. Loading and initial inspection of the USA census dataset (1994-1996)

In [3]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from scipy.stats import skew
import math
from sklearn.model_selection import train_test_split, GridSearchCV
from xgboost import XGBClassifier
from sklearn.ensemble import AdaBoostClassifier, RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, accuracy_score, precision_scor
from imblearn.over_sampling import SMOTE
```

In [4]:
```
df = pd.read_csv('adult.data')
```

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

Out[5]:

	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	M
0	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	
1	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	
2	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	
3	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Fe
4	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	Wife	White	Fe

In [6]:
```
headers = ['age','workclass','fnlwgt','education','education-num','marital-s
```

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In [7]:
```python
df.columns = headers
```

In [8]:
```python
df.head()
```

Out[8]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relati
0	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	H
1	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-ir
2	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	H
3	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	
4	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	

In [9]:
```python
df.describe()
```

Out[9]:

	age	fnlwgt	education-num	capital-gain	capital-loss
count	32560.000000	3.256000e+04	32560.000000	32560.000000	32560.000000
mean	38.581634	1.897818e+05	10.080590	1077.615172	87.306511
std	13.640642	1.055498e+05	2.572709	7385.402999	402.966116
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000
25%	28.000000	1.178315e+05	9.000000	0.000000	0.000000
50%	37.000000	1.783630e+05	10.000000	0.000000	0.000000
75%	48.000000	2.370545e+05	12.000000	0.000000	0.000000
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000

In [10]:
```python
df.shape
```

Out[10]:
```
(32560, 15)
```

In [11]:
```python
df.isnull().sum()
```

Out[11]:
```
age               0
workclass         0
fnlwgt            0
education         0
education-num     0
marital-status    0
occupation        0
relationship      0
race              0
sex               0
capital-gain      0
capital-loss      0
hours-per-week    0
native-country    0
Target            0
dtype: int64
```

In [12]:
```
df.dtypes
```

Out[12]:
```
age                int64
workclass         object
fnlwgt             int64
education         object
education-num      int64
marital-status    object
occupation        object
relationship      object
race              object
sex               object
capital-gain       int64
capital-loss       int64
hours-per-week     int64
native-country    object
Target            object
dtype: object
```

1.2. Exploratory data analysis

In [13]:
```
df['Target'].unique()
```

Out[13]:
```
array([' <=50K', ' >50K'], dtype=object)
```

In [14]:
```
more_than_50k = df[df['Target'].str.strip()=='>50K']
less_than_50k = df[df['Target'].str.strip()=='<=50K']
```

1.2.1. Distribution analysis of continuous variables

In [15]:
```
plt.figure(figsize=(10,6))
sns.kdeplot(data = more_than_50k,x='age' ,label='>50k', fill=True )
sns.kdeplot(data=less_than_50k,x='age', label='<50k', fill= True)
plt.title('Age Distribution of People Earning More vs Less than 50K')
plt.xlabel('Age')
l('Density')
```

```python
plt.legend()

# Show the plot
plt.show()
```

In [16]:
```python
more_than_50k.shape
```
Out[16]: (7841, 15)

In [17]:
```python
less_than_50k.shape
```
Out[17]: (24719, 15)

Key Take away from this plot

Younger individuals (below 30) are more likely to earn less than $50K.
 Older individuals (around 50+) are more likely to earn more than $50K.
There is a positive correlation between age and earning.

In [18]:
```python
more_than_50k['hours-per-week'].mean()
```
Out[18]: 45.473026399693914

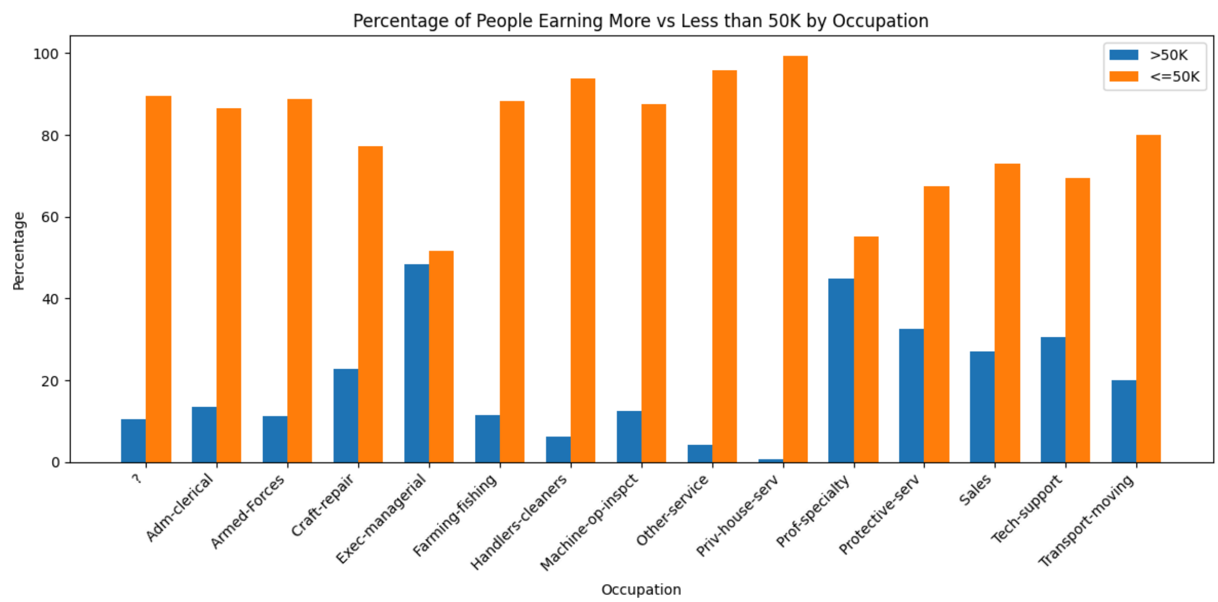
In [19]:
```python
less_than_50k['hours-per-week'].mean()
```
Out[19]: 38.840163437032245

In [20]:
```python
df['occupation'].unique()
```

```
Out[20]: array([' Exec-managerial', ' Handlers-cleaners', ' Prof-specialty',
       ' Other-service', ' Adm-clerical', ' Sales', ' Craft-repair',
       ' Transport-moving', ' Farming-fishing', ' Machine-op-inspct',
       ' Tech-support', ' ?', ' Protective-serv', ' Armed-Forces',
       ' Priv-house-serv'], dtype=object)
```

```
In [21]: occupation_counts = more_than_50k['occupation'].value_counts()
total_occupation_value = df['occupation'].value_counts()
percent_occupation = (occupation_counts/total_occupation_value)*100
occupation_less_than_50k = (less_than_50k['occupation'].value_counts() / df[
occupation_comparison = pd.DataFrame({
    '>50K': percent_occupation,
    '<=50K': occupation_less_than_50k
})
occupation_comparison = occupation_comparison.dropna()
fig, ax = plt.subplots(figsize=(12, 6))
bar_width = 0.35
index = np.arange(len(occupation_comparison))
bar1 = ax.bar(index, occupation_comparison['>50K'], bar_width, label='>50K')
bar2 = ax.bar(index + bar_width, occupation_comparison['<=50K'], bar_width,
ax.set_xlabel('Occupation')
ax.set_ylabel('Percentage')
ax.set_title('Percentage of People Earning More vs Less than 50K by Occupati
ax.set_xticks(index + bar_width / 2)
ax.set_xticklabels(occupation_comparison.index, rotation=45, ha='right')
ax.legend()

# Show the plot
plt.tight_layout()
plt.show()
```




```
In [22]: # Calculate percentage and sort by index (education-num) to ensure correct c
percent_of_people = (more_than_50k['education-num'].value_counts() / df['edu

# Plotting the data
plt.figure(figsize=(10,6))
ax = percent_of_people.plot(kind='bar', color='skyblue', label='>50K Percent
```

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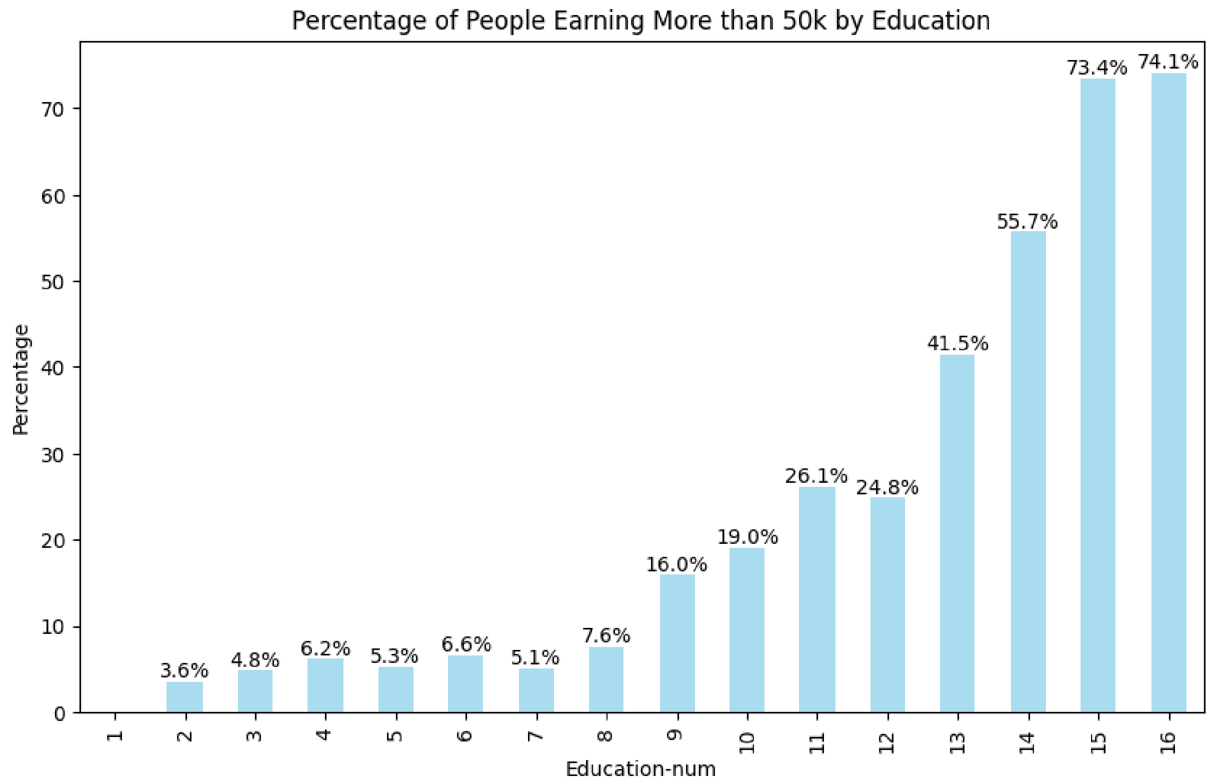
```
# Adding percentage labels athe bars
for i, percent in enumerate(percent_of_people):
    ax.text(i, percent + 0.5, f'{percent:.1f}%', ha='center', fontsize=10, c

# Titles and labels
plt.title('Percentage of People Earning More than 50k by Education')
plt.xlabel('Education-num')
plt.ylabel('Percentage')
plt.show()
```

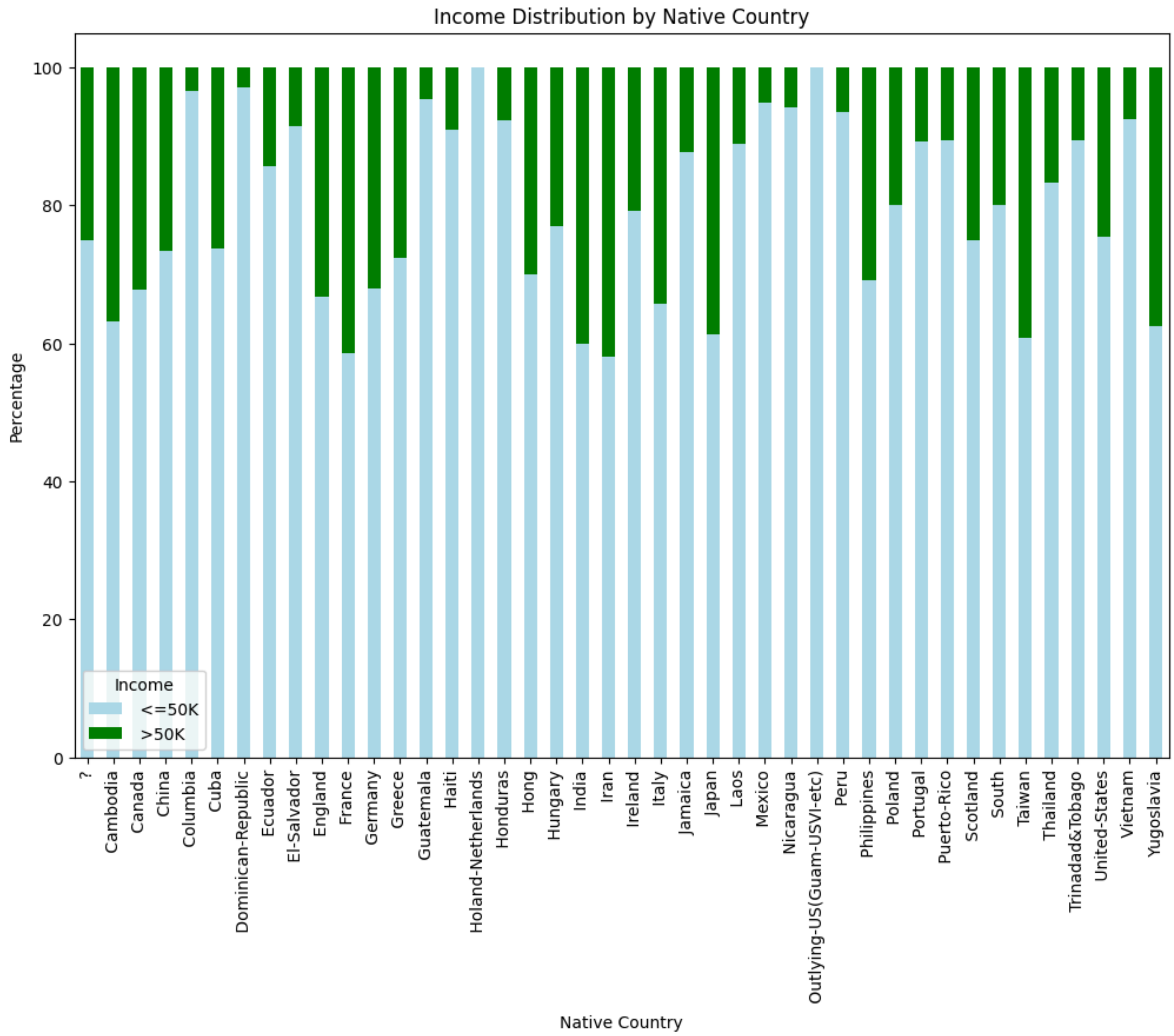
```
posx and posy should be finite values
posx and posy should be finite values
```



In [23]:
```
# Group data by native-country and income
country_income = df.groupby(['native-country', 'Target']).size().unstack().f

# Normalize the data to show percentages
country_income = country_income.div(country_income.sum(axis=1), axis=0) * 10

# Plot stacked bar chart
country_income.plot(kind='bar', stacked=True, figsize=(12,8), color=['lightb
plt.title('Income Distribution by Native Country')
plt.xlabel('Native Country')
plt.ylabel('Percentage')
plt.legend(title='Income')
plt.xticks(rotation=90)
plt.show()
```



In [24]:
```
capital_gain_more_than_50K = more_than_50k['capital-gain'].mean()
capital_gain_less_than_50K = less_than_50k['capital-gain'].mean()
capital_loss_more_than_50K = more_than_50k['capital-loss'].mean()
capital_loss_less_than_50K = less_than_50k['capital-loss'].mean()


categories = ['Capital Gain', 'Capital Loss']
more_than_50K = [capital_gain_more_than_50K, capital_loss_more_than_50K]
less_than_50K = [capital_gain_less_than_50K, capital_loss_less_than_50K]

x = np.arange(len(categories))


bar_width = 0.35

fig, ax = plt.subplots()
bar1 = ax.bar(x - bar_width/2, more_than_50K, bar_width, label='> 50K', colo
bar2 = ax.bar(x + bar_width/2, less_than_50K, bar_width, label='< 50K', colo


ax.set_xlabel('Categories')
ax.set_ylabel('Average Values')
ax.set_title('Comparison of Capital Gain and Loss for Income Groups')
```

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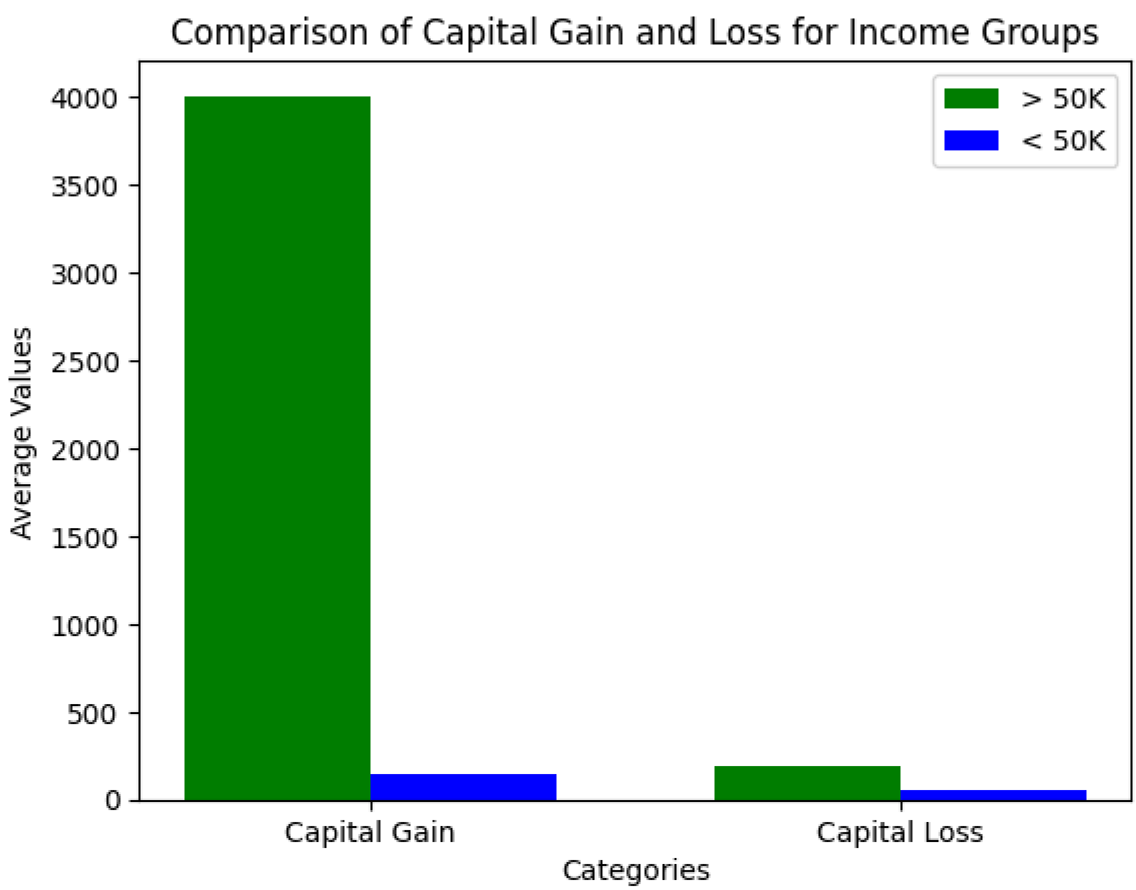
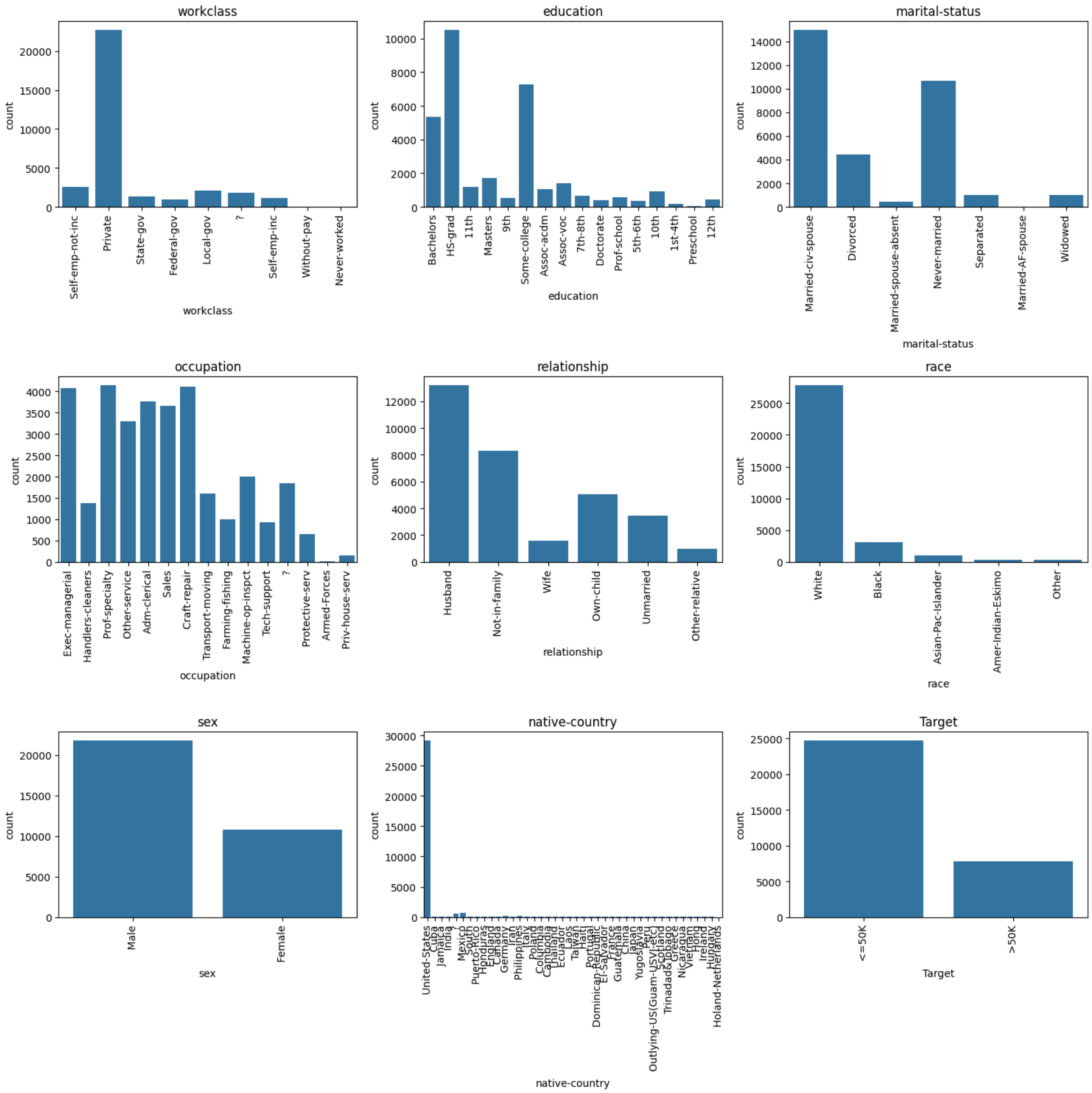
```
ax.set_xticks(x)
ax.set_xticklabels(categories)
ax.legend()


plt.show()
```



In [25]:

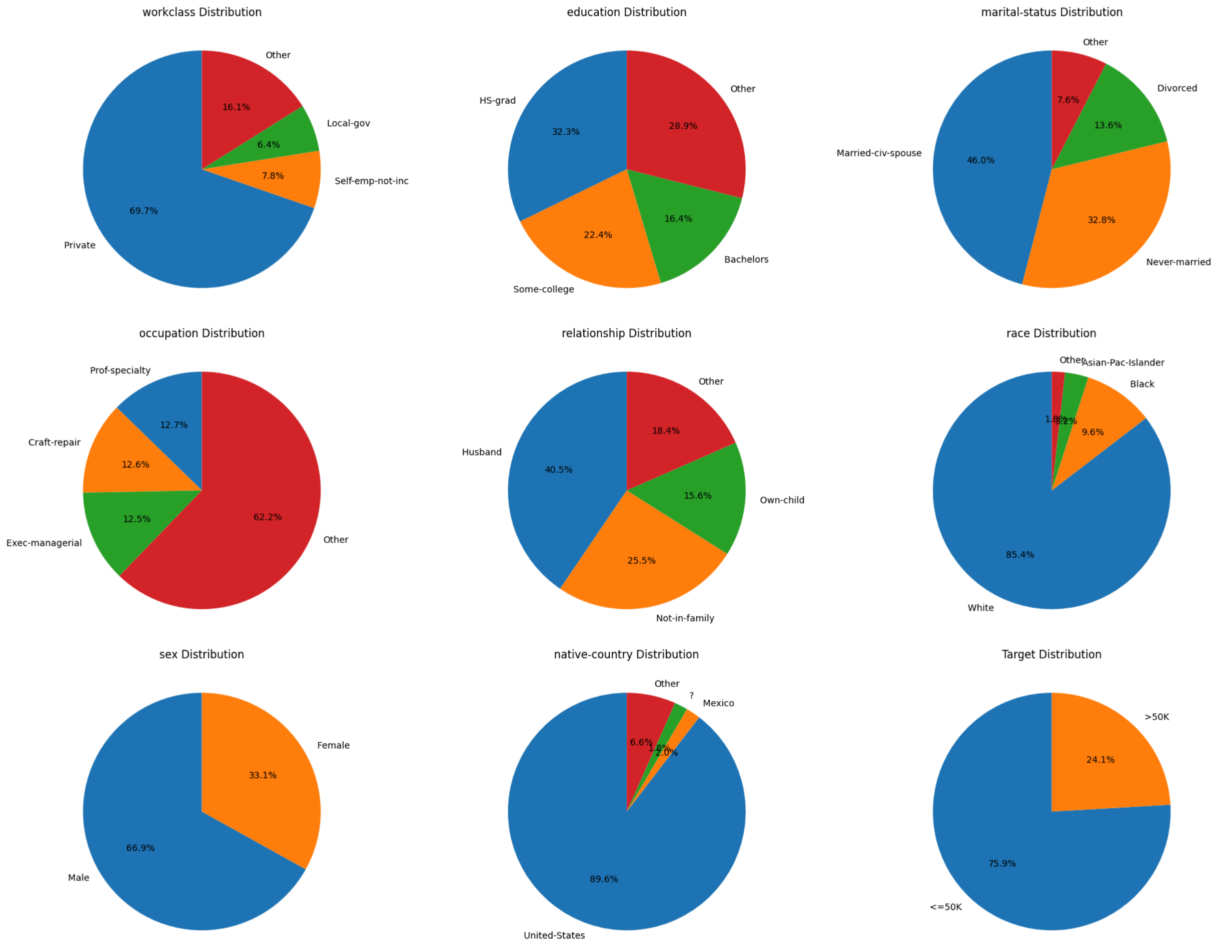
```
# Get the names of all columns with data type 'object' (categorical columns)
cat_vars = df.select_dtypes(include='object').columns.tolist()

# Create a figure with subplots
num_cols = len(cat_vars)
num_rows = (num_cols + 2) // 3
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Create a countplot for the top 6 values of each categorical variable using
for i, var in enumerate(cat_vars):
    top_values = df[var].value_counts().index
    filtered_df = df[df[var].isin(top_values)]
    sns.countplot(x=var, data=filtered_df, ax=axs[i])
    axs[i].set_title(var)
    axs[i].tick_params(axis='x', rotation=90)

# Remove any extra empty subplots if needed
if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])
```

```
# Adjust spacing between subplots
fig.tight_layout()

# Show plot
plt.show()
```



In [26]:
```
max_categories = 3

# Filter categorical columns with 'object' data type
cat_cols = [col for col in df.columns if col != 'y' and df[col].dtype == 'ob

# Create a figure with subplots
num_cols = len(cat_cols)
num_rows = (num_cols + 2) // 3
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(20, 5*num_rows))

# Flatten the axs array for easier indexing
axs = axs.flatten()
```

```python
# Create a pie chart for each categorical column
for i, col in enumerate(cat_cols):
    if i < len(axs):  # Ensure we don't exceed the number of subplots
        # Count the number of occurrences for each category
        cat_counts = df[col].value_counts()

        # Group categories beyond the top max_categories as 'Other'
        if len(cat_counts) > max_categories:
            cat_counts_top = cat_counts.nlargest(max_categories)
            other_count = cat_counts.sum() - cat_counts_top.sum()
            cat_counts_final = pd.concat([cat_counts_top, pd.Series({'Other'
        else:
            cat_counts_final = cat_counts

        # Create a pie chart
        axs[i].pie(cat_counts_final.values, labels=cat_counts_final.index, a
        axs[i].set_title(f'{col} Distribution')

# Remove any extra empty subplots if needed
if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])

# Adjust spacing between subplots
plt.tight_layout()

# Show plot
plt.show()
```



1.3.2. Skewness assessment of continuous variables

In [27]:

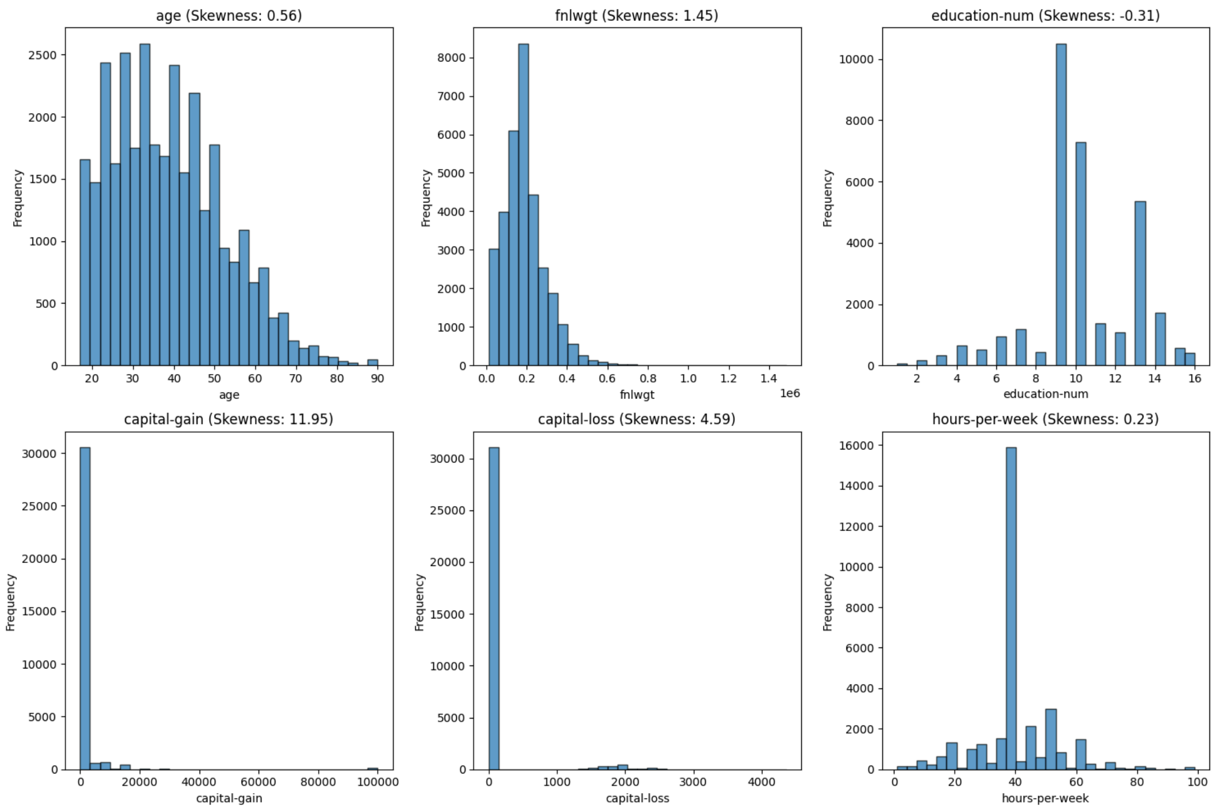
```
continuous_columns = df.select_dtypes(include=['int64','float64']).columns
skewness_values = {}
for col in continuous_columns:
        skew_data = skew(df[col])
        skewness_values[col] = skew_data
        print(f'skewness of {col}: {skew_data}')
```

```
skewness of age: 0.5587118988154982
skewness of fnlwgt: 1.4469055818253151
skewness of education-num: -0.31161553498633193
skewness of capital-gain: 11.953139157554617
skewness of capital-loss: 4.594337190555792
skewness of hours-per-week: 0.2276253044722967
```

In [28]:

```
# Number of rows and columns for subplots
n_rows = math.ceil(len(continuous_columns) / 3)  # 3 columns per row
fig, axes = plt.subplots(n_rows, 3, figsize=(15, 5 * n_rows))  # Correct pl

# Flatten axes if necessary
if n_rows == 1 and len(continuous_columns) <= 3:
    axes = axes.flatten()  # If only 1 row, treat it as a 1D array
elif n_rows > 1:
```

```
    axes = axes.flatten()  # For multiple rows, always flatten

# Plot histograms with skewness
for i, col in enumerate(continuous_columns):
    ax = axes[i]
    ax.hist(df[col].dropna(), bins=30, edgecolor='k', alpha=0.7)
    ax.set_title(f'{col} (Skewness: {skewness_values[col]:.2f})')
    ax.set_xlabel(col)
    ax.set_ylabel('Frequency')


#for j in range(i + 1, len(axes)):
 #    fig.delaxes(axes[j])

# Adjust the layout to prevent overlap
plt.tight_layout()
plt.show()
```



1.2.2. Skewness transformation of continuous variables

In [29]:
```
df['capital_gain_flag'] = np.where(df['capital-gain']> 0, 1, 0)
df['capital_gain_log'] = np.where(df['capital-gain'] > 0, np.log(df['capital
  
df['capital_loss_flag'] = np.where(df['capital-loss'] > 0, 1, 0)
df['capital_loss_log']  = np.where(df['capital-loss'] > 0, np.log(df['capita

df.head()
```

Out[29]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relati
0	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	H
1	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-ir
2	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	H
3	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	
4	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	

In [30]:
```
df = df.drop(columns=['capital-gain','capital-loss'], axis = 1)
```

Data Preprocessing

2.1. Feature encoding for categorical variables

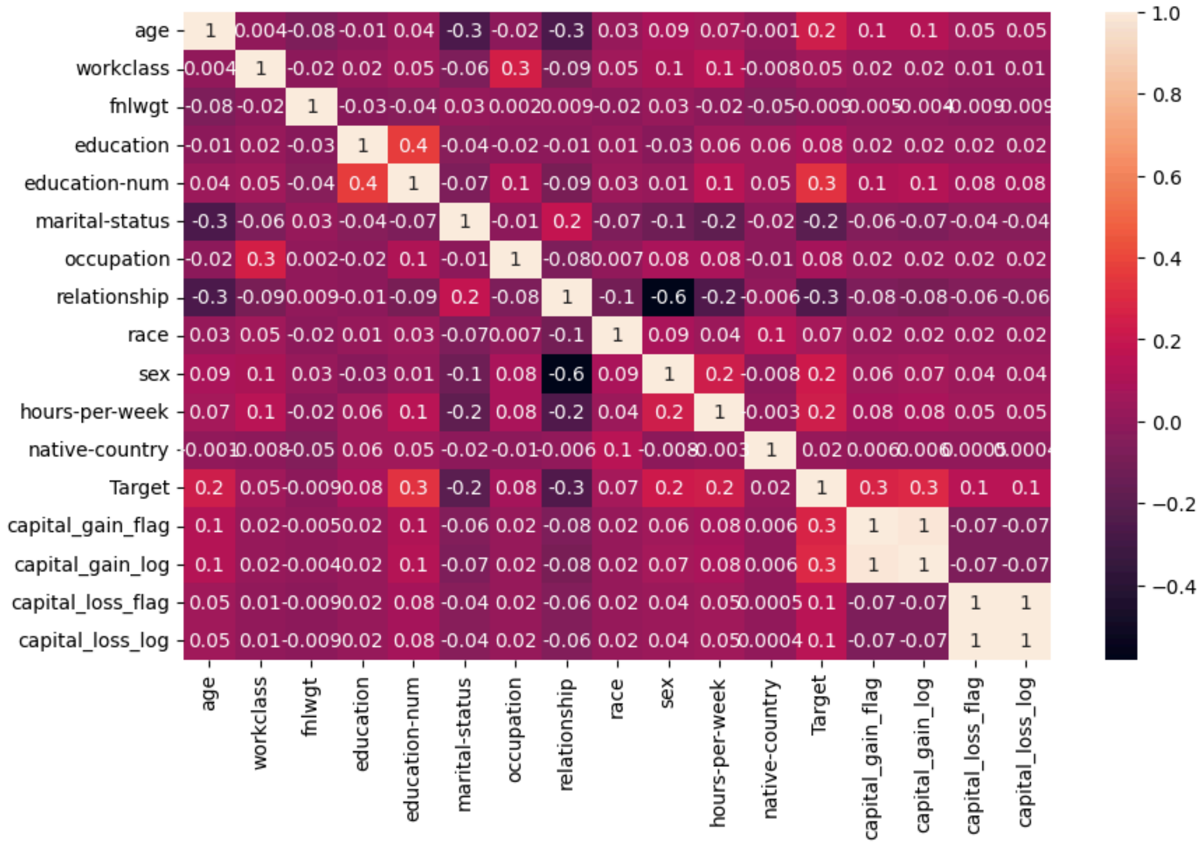
In [38]:
```
from sklearn import preprocessing
for col in df.select_dtypes(include='object').columns:
    label_encoder = preprocessing.LabelEncoder()
    label_encoder.fit(df[col].unique())
    df[col] = label_encoder.transform(df[col])
    print(f'{col} {df[col].unique()}')
```

```
workclass [6 4 7 1 2 0 5 8 3]
education [ 9 11  1 12  6 15  7  8  5 10 14  4  0  3 13  2]
marital-status [2 0 3 4 5 1 6]
occupation [ 4  6 10  8  1 12  3 14  5  7 13  0 11  2  9]
relationship [0 1 5 3 4 2]
race [4 2 1 0 3]
sex [1 0]
native-country [39  5 23 19  0 26 35 33 16  9  2 11 20 30 22 31  4  1 37  7
25 36 14 32
  6  8 10 13  3 24 41 29 28 34 38 12 27 40 17 21 18 15]
Target [0 1]
```

1.3.3. Correlation analysis using heatmap visualization

In [30]:
```
plt.figure(figsize=(10,6))
sns.heatmap(df.corr(),fmt='.1g',annot=True)
```

Out[30]: <Axes: >



2.2. Standardization of numerical features

In [40]:

```
continuous_feature = df.select_dtypes(include=['int64','float64']).columns
continuous_df = df.loc[:,continuous_feature]
categorical_feature = df.select_dtypes(include=['int32','object']).columns
categorical_df = df.loc[:,categorical_feature]

from sklearn.preprocessing import StandardScaler
sacaler = StandardScaler()
scaled_data = sacaler.fit_transform(continuous_df)
scaled_df = pd.DataFrame(scaled_data, columns=continuous_df.columns)
Standard_df = pd.concat([scaled_df, categorical_df.reset_index(drop=True)],
Standard_df.head()
```

Out[40]:

	age	fnlwgt	education-num	hours-per-week	capital_gain_log	capital_loss_log
0	0.837097	-1.008742	1.134779	-2.22212	-0.299216	-0.221078
1	-0.042640	0.245046	-0.420027	-0.03543	-0.299216	-0.221078
2	1.057031	0.425770	-1.197429	-0.03543	-0.299216	-0.221078
3	-0.775755	1.408146	1.134779	-0.03543	-0.299216	-0.221078
4	-0.115952	0.898170	1.523480	-0.03543	-0.299216	-0.221078

In [41]:
```
continuous_df.head()
```

Out[41]:

	age	fnlwgt	education-num	hours-per-week	capital_gain_log	capital_loss_log
0	50	83311	13	13	0.0	0.0
1	38	215646	9	40	0.0	0.0
2	53	234721	7	40	0.0	0.0
3	28	338409	13	40	0.0	0.0
4	37	284582	14	40	0.0	0.0

2.3. Dataset splitting into training and testing sets

In [42]:
```
X = Standard_df.drop('Target', axis=1)
y = Standard_df['Target']
```

In [43]:
```
X_train_, X_test, y_train_, y_test = train_test_split(X,y, test_size = 0.2,
```

In [44]:
```
unique_categories, counts = np.unique(y_train_, return_counts=True)
print("\nCounts of each category:")
print(counts)
```

```
Counts of each category:
[19762  6286]
```

3.2. Implementation of SMOTE (Synthetic Minority Over-sampling Technique)

In [45]:
```
smot = SMOTE(random_state=42)
X_train , y_train = smot.fit_resample(X_train_, y_train_)
```

In [46]:
```
unique_categories, counts = np.unique(y_train, return_counts=True)
print("\nCounts of each category:")
print(counts)
```

```
Counts of each category:
[19762 19762]
```

Initial Model Development

4.1. Training a baseline model using all features

In [47]:
```
log_reg = LogisticRegression()
```

In [48]:
```
log_reg.fit(X_train,y_train)
```

```
C:\Users\Dell\AppData\Roaming\Python\Python311\site-packages\sklearn\linear_
model\_logistic.py:469: ConvergenceWarning: lbfgs failed to converge (status
=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regre
ssion
  n_iter_i = _check_optimize_result(
```

Out[48]:
```
▼ LogisticRegression
LogisticRegression()
```

4.2. Evaluation of model performance

In [49]:
```
y_pred = log_reg.predict(X_test)
```

4.2.1. Accuracy assessment

In [50]:
```
accuracy = accuracy_score(y_test, y_pred)
print(f'accuracy :{accuracy*100:.2f}%')
```

```
accuracy :77.60%
```

4.2.2. Additional relevant metrics (precision, recall, F1-score)

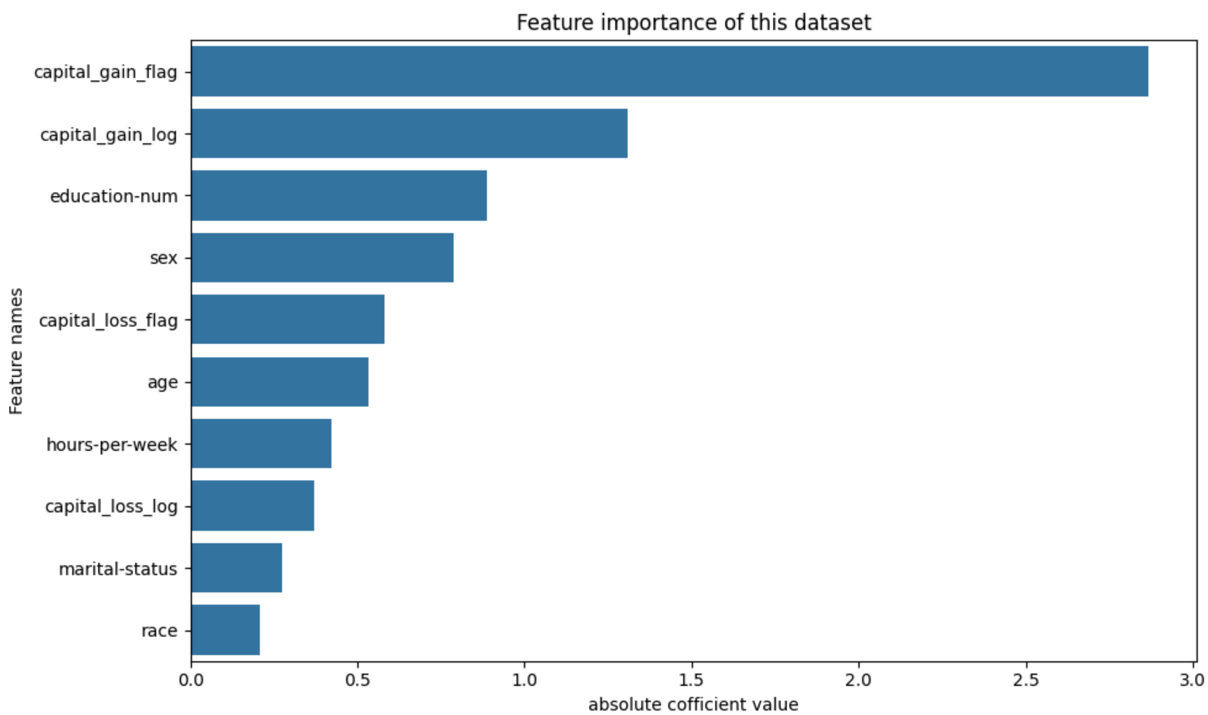
In [51]:
```
cla_report = classification_report(y_pred, y_test)
print('Classification report \n' ,cla_report  )
```

```
Classification report
               precision    recall  f1-score   support

           0       0.77      0.92      0.84      4154
           1       0.79      0.52      0.63      2358

    accuracy                           0.78      6512
   macro avg       0.78      0.72      0.73      6512
weighted avg       0.78      0.78      0.76      6512
```

Feature Engineering and Selection

5.1. Feature importance analysis using coefficient magnitude

In [43]:
```
importances = np.abs(log_reg.coef_[0])
imp_df = pd.DataFrame({"feature_name" : X_train.columns,
          "importance":importances})
fi = imp_df.sort_values(by="importance", ascending=False)

top_features = fi.head(10)
plt.figure(figsize=(10,6))
sns.barplot(data = top_features, x='importance', y='feature_name')
plt.title('Feature importance of this dataset')
plt.xlabel('absolute cofficient value')
plt.ylabel('Feature names')
plt.tight_layout()
plt.show()
```



5.2. Selection of top contributing features

In [44]:
```
top_feature_names = top_features['feature_name'].tolist()
X_train_reduced = X_train[top_feature_names]
X_test_reduced = X_test[top_feature_names]
```

5.3. Model retraining with selected features

In [45]:
```
log_reg_1 = LogisticRegression()
```

Loading [MathJax]/extensions/Safe.js

```
In [46]: log_reg_1.fit(X_train_reduced, y_train)
```

```
Out[46]: ▼ LogisticRegression
LogisticRegression()
```

```
In [47]: y_pred_1 = log_reg_1.predict(X_test_reduced)
```

5.4. Comparative analysis of model performance pre- and post-feature engineering

```
In [48]: accuracy_1 = accuracy_score(y_test, y_pred_1)
print(f'accuracy:{accuracy_1*100:.2f}')
```

```
accuracy:77.81
```

Accuracy is same before and after the feature engineering it means our feature engineering works

Advanced Modeling Techniques

6.1 Grid search for optimal hyperparameters

```
In [49]: param_grid = {
    'C': [0.01, 0.1, 1, 10, 100],
    'penalty': ['l1', 'l2'],  # 'liblinear' supports only 'l1' and 'l2' pena
    'solver': ['liblinear'],  # limit to 'liblinear' for 'l1' and 'l2' penal
    'max_iter': [100, 200, 300]
}

# Add a second grid for saga solver with elasticnet and no regularization su
param_grid_saga = {
    'C': [0.01, 0.1, 1, 10, 100],
    'penalty': ['l1', 'l2', 'elasticnet', None],  # Use 'none' as a string i
    'solver': ['saga'],  # 'saga' supports 'l1', 'l2', 'elasticnet', and 'nc
    'max_iter': [100, 200, 300],
    'l1_ratio': [0.5]  # required for 'elasticnet' penalty
}

# Use both parameter grids in a list
grid_search = GridSearchCV(
    LogisticRegression(),
    [param_grid, param_grid_saga],
    cv=5,
    scoring='accuracy',
    n_jobs=-1,
    error_score='raise'  # will raise errors if there are invalid parameter
)
```

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```
# Fit the model
grid_search.fit(X_train_reduced, y_train)

# Output the best parameters
print(f'Best parameter: {grid_search.best_params_}')
```

```
Best parameter: {'C': 1, 'max_iter': 200, 'penalty': 'l1', 'solver': 'liblin
ear'}
```

6.1.2 Logistic Regression with Hyperparameter Tuning

In [50]:
```
best_log_reg = LogisticRegression(
    C = 100, max_iter=200, penalty= 'l1', solver= 'liblinear'
)
best_log_reg.fit(X_train_reduced,y_train)
```

```
C:\Users\Dell\AppData\Roaming\Python\Python311\site-packages\sklearn\svm\_ba
se.py:1235: ConvergenceWarning: Liblinear failed to converge, increase the n
umber of iterations.
  warnings.warn(
```

Out[50]:
```
LogisticRegression

LogisticRegression(C=100, max_iter=200, penalty='l1', solver='libli
near')
```

6.1.3 Model performance evaluation with tuned parameters

In [51]:
```
y_pred_best = best_log_reg.predict(X_test_reduced)
print(f'Accuracy : {accuracy_score(y_pred_best, y_test)*100:.2f}')
```

```
Accuracy : 78.15
```

In [52]:
```
print(f'Precision of the Model : {precision_score(y_test, y_pred_best):.2f}'
```

```
Precision of the Model : 0.53
```

6.2. XGBoost Algorithm Implementation

In [70]:
```
scale_weight_pos = sum(y_train == 0)/sum(y_train == 1)
```

In [71]:
```
xgb_clf = XGBClassifier(
    objective = 'binary:logistic',
    scale_pos_weight = scale_weight_pos,
    learning_rate = 0.1,
    max_depth = 6,
    n_estimators = 100,
    use_label_encoder = False,
    eval_metric = 'logloss'
)
```

6.2.1. Initial XGBoost model training

In [72]:
```
xgb_clf.fit(X_train_reduced,y_train)
```

Out[72]:

▾ XGBClassifier

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_ro
unds=None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=0.1, max_bin=None, max_cat_threshold=No
ne,
```

In [73]:
```
xgb_pred = xgb_clf.predict(X_test_reduced)
```

6.2.2. Performance evaluation of optimized XGBoost model

In [78]:
```
print("Classification Report:\n", classification_report(y_test, xgb_pred))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.94      0.85      0.89      4957
           1       0.63      0.82      0.71      1555

    accuracy                           0.84      6512
   macro avg       0.78      0.83      0.80      6512
weighted avg       0.86      0.84      0.85      6512
```

6.2.3. Hyperparameter tuning for XGBoost

In [79]:
```python
from sklearn.model_selection import GridSearchCV

param_grid = {
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 6, 10],
    'n_estimators': [100, 200, 300],
    'subsample': [0.8, 1],
    'colsample_bytree': [0.8, 1],
    'gamma': [0, 1, 5]
}

grid_search = GridSearchCV(estimator=xgb_clf, param_grid=param_grid,
                           scoring='f1', cv=5, n_jobs=-1, verbose=2)
```

In [80]:
```python
grid_search.fit(X_train_reduced, y_train)
```

```
Fitting 5 folds for each of 324 candidates, totalling 1620 fits
```

Out[80]:
```
▸ GridSearchCV
▸ best_estimator_: XGBClassifier
▸ XGBClassifier
```

In [84]:
```python
best_params = grid_search.best_params_
xgb_best = XGBClassifier(**best_params)
xgb_best.fit(X_train_reduced, y_train)
```

Out[84]:
```
▾ XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.8, device=None, early_stopping_rou
nds=None,
              enable_categorical=False, eval_metric=None, feature_t
ypes=None,
              gamma=0, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_
bin=None,
```

In [85]:
```python
xgb_pred = xgb_best.predict(X_test_reduced)
```

6.2. Performance evaluation of optimized XGBoost model

In [86]:
```python
print("Classification Report:\n", classification_report(y_test, xgb_pred))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.89      0.90      4957
           1       0.67      0.73      0.70      1555

    accuracy                           0.85      6512
   macro avg       0.79      0.81      0.80      6512
weighted avg       0.85      0.85      0.85      6512
```

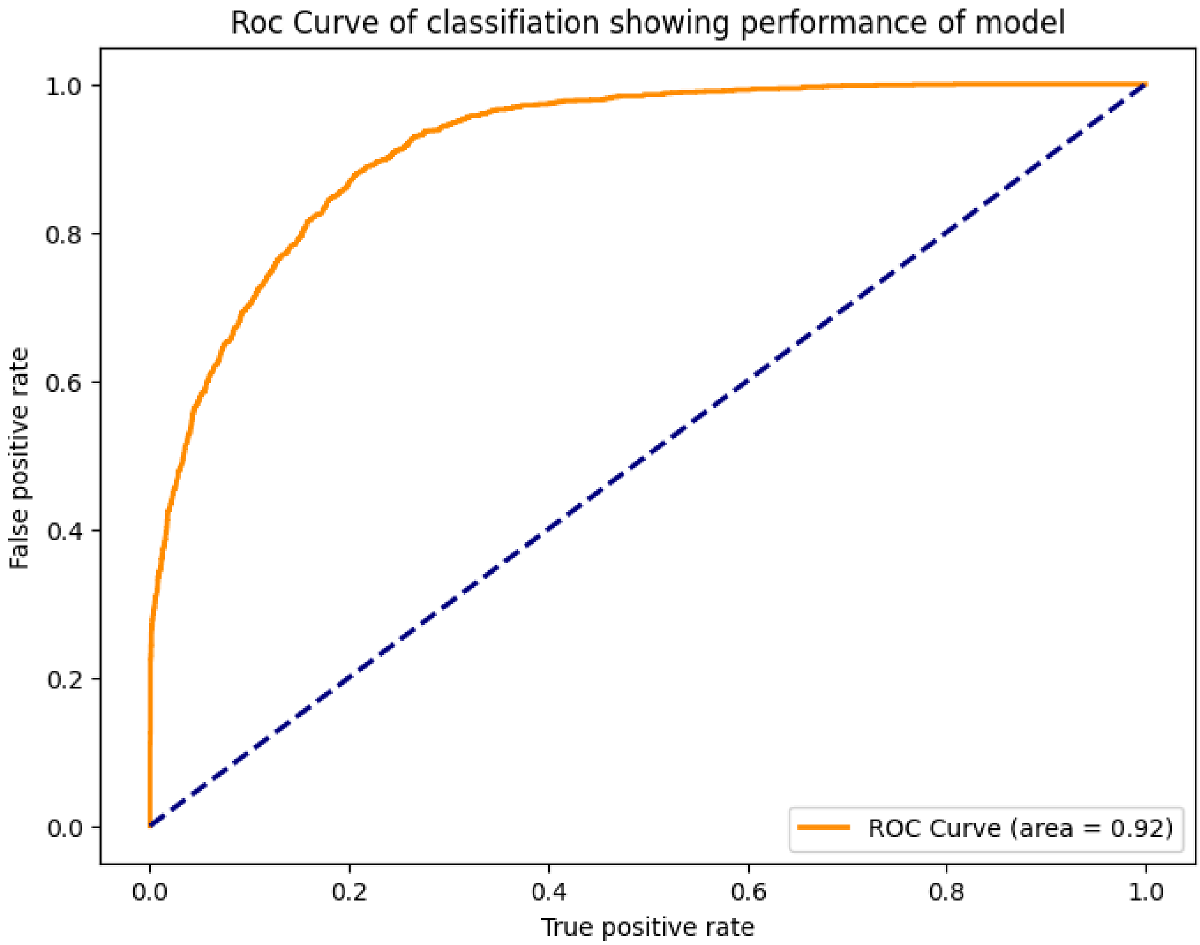
In [108…

```
result_df = pd.DataFrame(
{'Actual': y_test,
'Predicted' : xgb_pred})
```

7.1. ROC curve analysis for model performance

In [118…

```
y_pred_prob = xgb_best.predict_proba(X_test_reduced)[:,1]
fpr, tpr , thresholds = roc_curve(y_test, y_pred_prob)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC Curve (area = {roc_
plt.plot([0, 1],[0, 1] , color = 'navy', lw =2, linestyle = '--')
plt.title('Roc Curve of classifiation showing performance of model')
plt.xlabel('True positive rate')
plt.ylabel('False positive rate')
plt.legend(loc='lower right')
plt.show()
```



Below is the detailed report of Data Science Project key insights and model Training Results

Data Science Project Report

1. Introduction

The goal of this analysis is to determine the factors influencing whether an individual earns more or less than $50K. Using various machine learning techniques, including feature engineering, logistic regression, and ensemble methods like XGBoost, we evaluate performance through classification metrics like accuracy, AUC, and more.

2 Exploratory Data Analysis (EDA)

2.1 Capital Gain and Loss: Risk Appetite of High Earners

Individuals who earn more than $50K show higher levels of capital gains and losses, suggesting a higher tolerance for financial risk. Here are the mean values observed:

- **Capital Gain (>50K)**: 4006.14
- **Capital Gain (<50K)**: 148.67
- **Capital Loss (>50K)**: 195.00
- **Capital Loss (<50K)**: 53.15

Capital gain vs Capital loss

2.2 Age Distribution and Earnings

There is a positive correlation between age and earning potential. Younger individuals (below 30) tend to earn less than $50K, while older individuals (around 50 or higher) are more likely to earn more.

Age Distribution

2.3 Correlation Between Education and Earnings

Higher education levels correspond to higher earnings. As the education level increases, the likelihood of earning more than $50K also increases.

Earning and Education

2.4 Country-Specific Insights

Certain countries have a higher proportion of individuals earning more than $50K. Leading countries include Iran, France, and India.

Income by Native Country

3. Data Preprocessing and Feature Engineering

Data preprocessing steps included:

- **Standardization**: Ensuring that all numerical features have the same scale.
- **Label Encoding**: For categorical variables.
- **Minimizing Skewness**: Handling outliers and transforming skewed features to approximate normal distributions.

Feature Engineering

Feature engineering was applied to derive meaningful features from the raw [illegible]nproving model performance.

Feature Engineering

4. Model Training and Evaluation

4.1 Logistic Regression

We used Logistic Regression as the baseline model for classification. The logistic regression model was trained using:

- **Hyperparameter tuning**: Conducted using GridSearchCV to optimize parameters such as regularization strength and solver.
- **SMOTE**: Applied to handle class imbalance in the dataset.

4.2 Ensemble Technique: XGBoost Classifier

XGBoost was employed to further boost classification performance. This method is highly efficient and handles imbalanced classes well.

4.3 Hyperparameter Tuning

GridSearchCV was utilized to find the optimal hyperparameters for the logistic regression and XGBoost classifiers.

4.4 Evaluation Metrics

The performance of the models was evaluated based on several metrics:

- **Accuracy**: 0.85
- **Precision**:
  - Class 0 (less than $50K): 0.91
  - Class 1 (more than $50K): 0.67
- **Recall**:
  - Class 0: 0.89
  - Class 1: 0.73
- **F1-Score**:
  - Class 0: 0.90
  - Class 1: 0.70
- **AUC Score**: 0.92

4.5 ROC Curve for XGBoost

The ROC curve for the XGBoost classifier illustrates the trade-off between the true positive rate and the false positive rate.

ROC Curve