Forcasting of Product X and Y volume

1.importing Libraries

In [10]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
```

In [80]:
```
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_percentage_error
import numpy as np
import joblib
```

2. Load the dataset

In [11]:
```
# Load the dataset for analysis
file_path = 'Interview_dataset_ANALYTICS_EXECUTIVE.xlsx'
data = pd.ExcelFile(file_path)
data
```

Out[11]:
```
<pandas.io.excel._base.ExcelFile at 0x2178bc27970>
```

In [12]:
```
df = data.parse('Sheet1')

# Display the first few rows
df.head()
```

Out[12]:

	DateTime	FY	Product- X Vol (000s)	Product- Y Vol(000s)	X $/Unit	Y $/unit	X conumers Mean Income	Y Consumers Mean Income	Alternative Category % in the market	Counterfeit % in the market
0	2013-05-01	FY 13	652079.4900	62274.96095	0.567842	0.658706	77.820000	72.030000	0.001862	0.196348
1	2013-06-01	FY 13	611646.5390	59483.67820	0.568119	0.658941	79.044167	67.198333	0.003841	0.193263
2	2013-07-01	FY 13	635476.3305	61545.88525	0.570166	0.660020	77.239353	66.547182	0.004032	0.190833
3	2013-08-01	FY 13	626186.9260	60533.70730	0.576185	0.672148	79.067234	67.015250	0.003861	0.191189
4	2013-09-01	FY 13	637616.4575	60135.61650	0.576996	0.673305	78.646856	66.913296	0.003923	0.190546

In [13]:
```
df.columns
```

Out[13]:
```
Index(['DateTime', 'FY', 'Product- X Vol (000s)', 'Product- Y  Vol(000s) ',
       'X  $/Unit', 'Y $/unit', 'X conumers Mean Income',
       'Y Consumers Mean Income', 'Alternative Category % in the market',
       'Counterfeit % in the market'],
      dtype='object')
```

3. Renaming columns

Columns were renamed to remove spaces and standardize names, improving code readability and reducing errors during processing.

In [15]:
```
# Renaming columns to standardize and remove extra spaces
df.rename(columns={
    'Product- X Vol (000s)': 'Product_X_Volume',
    'Product- Y  Vol(000s) ': 'Product_Y_Volume',
    'X  $/Unit': 'X_Price_Per_Unit',
    'Y $/unit': 'Y_Price_Per_Unit',
    'X conumers Mean Income': 'X_Consumers_Mean_Income',
    'Y Consumers Mean Income': 'Y_Consumers_Mean_Income',
    'Alternative Category % in the market': 'Alternative_Category_Percentage',
    'Counterfeit % in the market': 'Counterfeit_Percentage'
}, inplace=True)

df.columns
```

Out[15]:
```
Index(['DateTime', 'FY', 'Product_X_Volume', 'Product_Y_Volume',
       'X_Price_Per_Unit', 'Y_Price_Per_Unit', 'X_Consumers_Mean_Income',
       'Y_Consumers_Mean_Income', 'Alternative_Category_Percentage',
       'Counterfeit_Percentage'],
      dtype='object')
```

4. Correlation Matrix and Summary of the data

In [14]:
```
df['DateTime'] = pd.to_datetime(df['DateTime'])

# Basic statistical summary of the dataset
summary_stats = df.describe()

# Correlation matrix to identify relationships
correlation_matrix = df.corr()
```

```
C:\Users\bbsur\AppData\Local\Temp\ipykernel_17040\1220737383.py:8: FutureWarning: The default value of numeric_only in Data
Frame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of
numeric_only to silence this warning.
  correlation_matrix = df.corr()
```

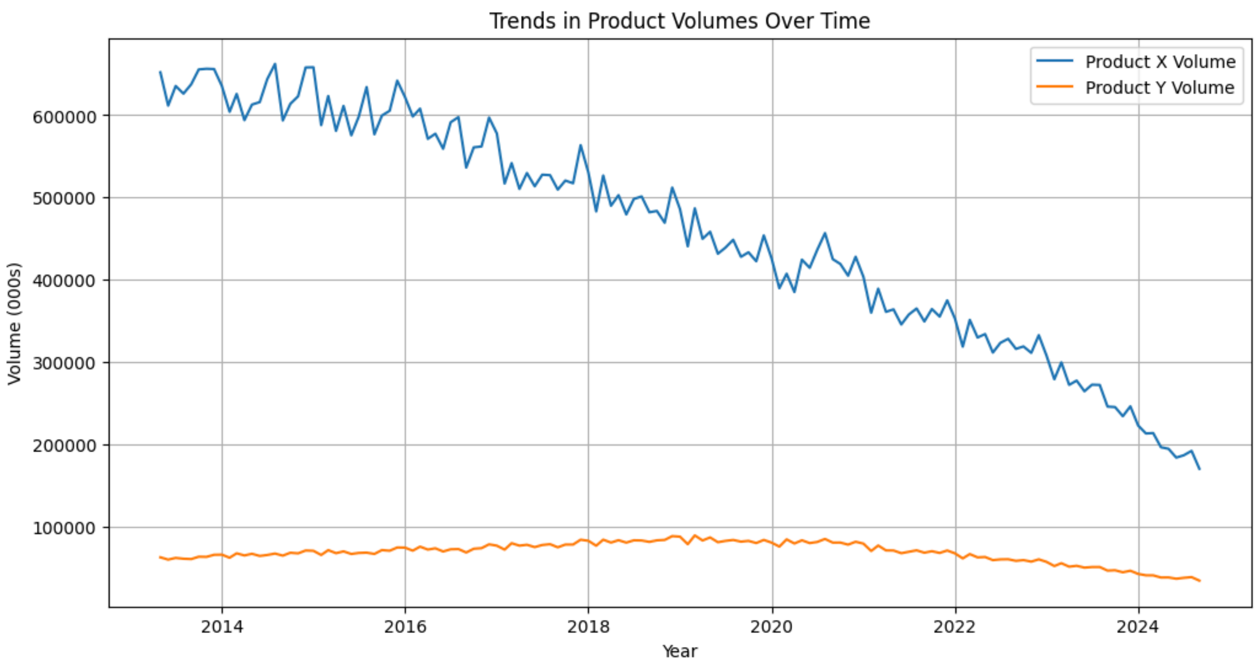
In [18]:
```
summary_stats
```

Out[18]:

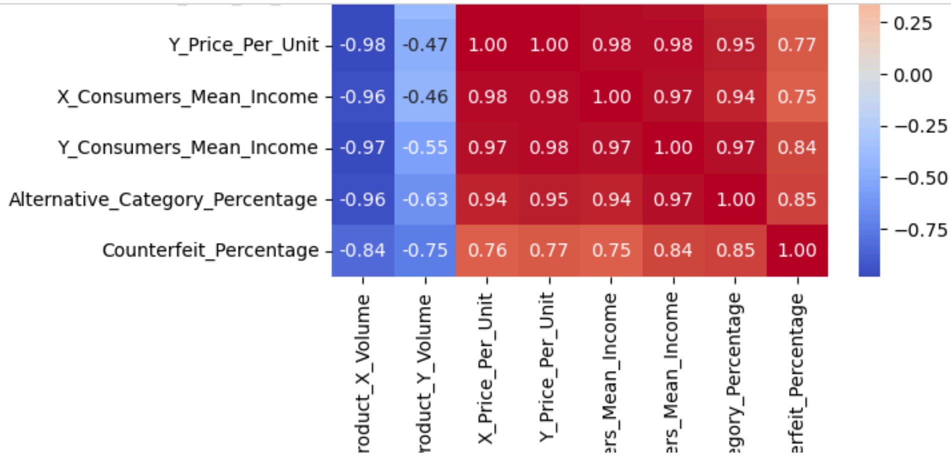
	Product- X Vol (000s)	Product- Y Vol(000s)	X $/Unit	Y $/unit	X conumers Mean Income	Y Consumers Mean Income	Alternative Category % in the market	Counterfeit % in the market
count	137.000000	137.000000	137.000000	137.000000	137.000000	137.000000	137.000000	137.000000
mean	459065.222481	68491.699604	1.087902	1.436181	98.666626	83.635369	0.178478	0.194670
std	137196.425365	12780.554743	0.342278	0.552836	16.443911	17.774600	0.166857	0.072541
min	169993.937500	33939.683595	0.567842	0.658706	77.239353	59.226625	0.001862	0.105206
25%	352503.906250	62213.562500	0.758904	0.927174	82.055094	67.198333	0.035309	0.135652
50%	479329.375000	70291.453150	1.073250	1.353292	97.998680	79.996489	0.105798	0.171103
75%	587822.812500	78931.562500	1.406736	1.965374	113.978967	99.593239	0.311380	0.229890
max	662407.698000	88922.289050	1.747776	2.589542	128.881617	116.395178	0.504019	0.392063

5. Plot the time series graph and correlation matrix

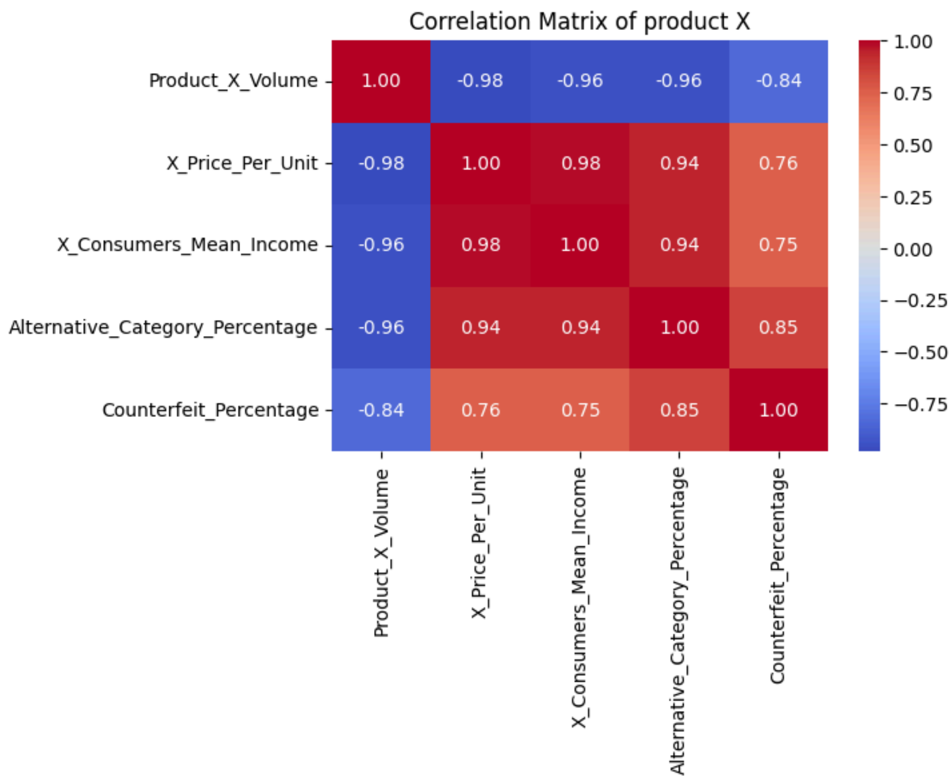
In [16]:
```
plt.figure(figsize=(12, 6))
plt.plot(df['DateTime'], df['Product_X_Volume'], label='Product X Volume')
plt.plot(df['DateTime'], df['Product_Y_Volume'], label='Product Y Volume')
plt.title('Trends in Product Volumes Over Time')
plt.xlabel('Year')
plt.ylabel('Volume (000s)')
plt.legend()
plt.grid()
plt.show()
```



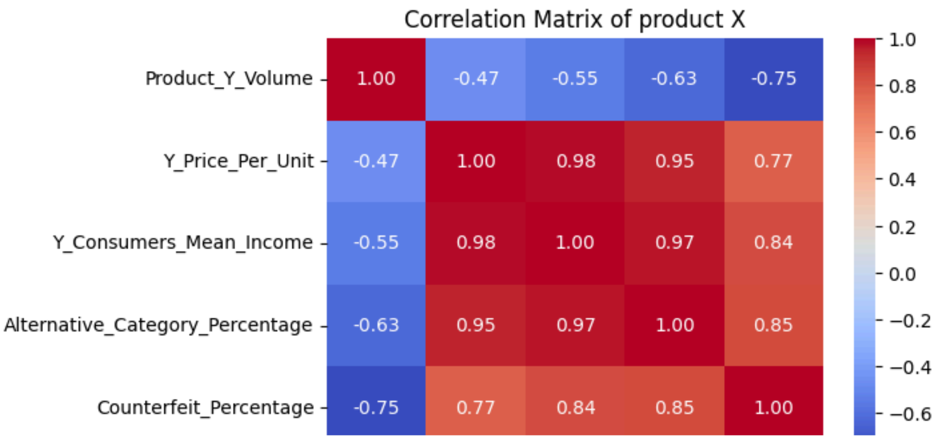
In [76]:
```
plt.figure(figsize=(6, 4))
sns.heatmap(df.corr(), annot=True, fmt=".2f", cmap="coolwarm")
plt.title('Correlation Matrix')
plt.show()
```



In [65]:
```
df1= df[['Product_X_Volume','X_Price_Per_Unit', 'X_Consumers_Mean_Income', 'Alternative_Category_Percentage', 'Counterfeit_P
plt.figure(figsize=(6, 4))
sns.heatmap(df1.corr(), annot=True, fmt=".2f", cmap="coolwarm")
plt.title('Correlation Matrix of product X')
plt.show()
```



In [66]:
```
df2= df[['Product_Y_Volume','Y_Price_Per_Unit', 'Y_Consumers_Mean_Income', 'Alternative_Category_Percentage', 'Counterfeit_Pe
plt.figure(figsize=(6,4))
sns.heatmap(df2.corr(), annot=True, fmt=".2f", cmap="coolwarm")
plt.title('Correlation Matrix of product X')
plt.show()
```



6. Feature Engineering and setting up parameters

For Product X:

X_Price_Per_Unit, X_Consumers_Mean_Income, Alternative_Category_Percentage, and Counterfeit_Percentage were selected as predictors.

For Product Y:

Alternative_Category_Percentage and Counterfeit_Percentage were selected, considering the minimal direct influence of price and income(less than .60 correlation).

In [77]:
```
# Define predictors and targetsfor both product X and Y
X = df[['X_Price_Per_Unit', 'X_Consumers_Mean_Income', 'Alternative_Category_Percentage', 'Counterfeit_Percentage']]
y_x = df['Product_X_Volume']
Y = df[[ 'Alternative_Category_Percentage', 'Counterfeit_Percentage']]
y_y = df['Product_Y_Volume']

# Split into training and testing sets for both product X and Y
X_train_x, X_test_x, y_train_x, y_test_x = train_test_split(X, y_x, test_size=0.2, random_state=42)
X_train_y, X_test_y, y_train_y, y_test_y = train_test_split(Y, y_y, test_size=0.2, random_state=42)

# Define the base model
# we are using the 2 different models
dt = DecisionTreeRegressor(random_state=42)
rid= Ridge()

# Set up the parameter grid for fine-tuning for both product X and Y
param_grid_dt = {
    'max_depth': [3, 5, 10, 15],
    'min_samples_split': [5, 10,  20, 50],
    'min_samples_leaf': [5, 7, 10, 20]
}

param_grid_rid={
    'alpha': [0.1, 1, 10],  # Regularization strength
    'fit_intercept': [True, False]}
```

7. Setup model fit and predict

In [78]:

```
# Perform grid search for Product X
grid_search_x = GridSearchCV(estimator=rid, param_grid=param_grid_rid, cv=5, scoring='neg_mean_squared_error', verbose=1)
grid_search_x.fit(X_train_x, y_train_x)

# Perform grid search for Product Y
grid_search_y = GridSearchCV(estimator=dt, param_grid=param_grid_dt, cv=5, scoring='neg_mean_squared_error', verbose=1)
grid_search_y.fit(X_train_y, y_train_y)

# Best parameters and models
best_model_x = grid_search_x.best_estimator_
best_model_y = grid_search_y.best_estimator_

# Predictions using the best models
y_pred_x = best_model_x.predict(X_test_x)
y_pred_y = best_model_y.predict(X_test_y)

# Evaluate the models
rmse_x = mean_squared_error(y_test_x, y_pred_x, squared=False)
mape_x = mean_absolute_percentage_error(y_test_x, y_pred_x)

rmse_y = mean_squared_error(y_test_y, y_pred_y, squared=False)
mape_y = mean_absolute_percentage_error(y_test_y, y_pred_y)

print("Fine-Tuned Model Performance:")
print(f"Product X - RMSE: {rmse_x:.2f}, MAPE: {mape_x:.2%}")
print(f"Product Y - RMSE: {rmse_y:.2f}, MAPE: {mape_y:.2%}")
```

```
Fitting 5 folds for each of 6 candidates, totalling 30 fits
Fitting 5 folds for each of 64 candidates, totalling 320 fits
Fine-Tuned Model Performance:
Product X - RMSE: 22777.63, MAPE: 4.20%
Product Y - RMSE: 3020.62, MAPE: 3.57%
```

9. Check the model on training data

By this we can confirm that that there was no major overfitting

In [79]:

```
# Evaluate the fine-tuned model on training data
train_pred_x = best_model_x.predict(X_train_x)
train_pred_y = best_model_y.predict(X_train_y)

train_rmse_x = mean_squared_error(y_train_x, train_pred_x, squared=False)
train_mape_x = mean_absolute_percentage_error(y_train_x, train_pred_x)

train_rmse_y = mean_squared_error(y_train_y, train_pred_y, squared=False)
train_mape_y = mean_absolute_percentage_error(y_train_y, train_pred_y)

print(f"Training Performance for Product X: RMSE: {train_rmse_x:.2f}, MAPE: {train_mape_x:.2%}")
print(f"Training Performance for Product Y: RMSE: {train_rmse_y:.2f}, MAPE: {train_mape_y:.2%}")
```

```
Training Performance for Product X: RMSE: 19466.44, MAPE: 3.88%
Training Performance for Product Y: RMSE: 2447.22, MAPE: 2.94%
```

10. Save the model

In [82]:

```
# Save the Ridge model (Product X)
joblib.dump(best_model_x, 'ridge_model_x.pkl')

# Save the Decision Tree model (Product Y)
joblib.dump(best_model_y, 'decision_tree_model_y.pkl')
```

Out[82]: ['decision_tree_model_y.pkl']

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