In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
sns.set_theme(color_codes=True)
pd.set_option('display.max_columns', None)
```

In [2]:
```
df = pd.read_csv('df_Clean.csv')
df.head()
```

Out[2]:

Issue	AC_1003_Issue	TV_2001_Issue	TV_2002_Issue	TV_2003_Issue	Claim_Value	Service_Centre	Product_Age	Purchased_from	Call_details	Pur
0	0	1	2	0	15000.0	10	60	Manufacturer	0.5	Com
1	0	0	0	0	20000.0	12	10	Dealer	1.0	Com
1	2	0	0	0	18000.0	14	10	Dealer	1.4	(
0	0	1	1	0	12000.0	16	20	Manufacturer	2.0	Com
0	0	0	1	2	25000.0	15	6	Dealer	1.3	(

Data Preprocessing Part 1

In [3]:
```
#Check the number of unique value from all of the object datatype
df.select_dtypes(include='object').nunique()
```

Out[3]:
```
Region              8
State              20
Area                2
City               27
Consumer_profile    2
Product_category    2
Product_type        2
Purchased_from      3
Purpose             3
dtype: int64
```

In [4]:
```
# Drop Unnamed : 0 column because this is identifier column
# Drop State and City column because there are alot of unique value. We can use Region column instead City and State
df.drop(columns=['Unnamed: 0', 'State', 'City'], inplace=True)
df.head()
```

Out[4]:

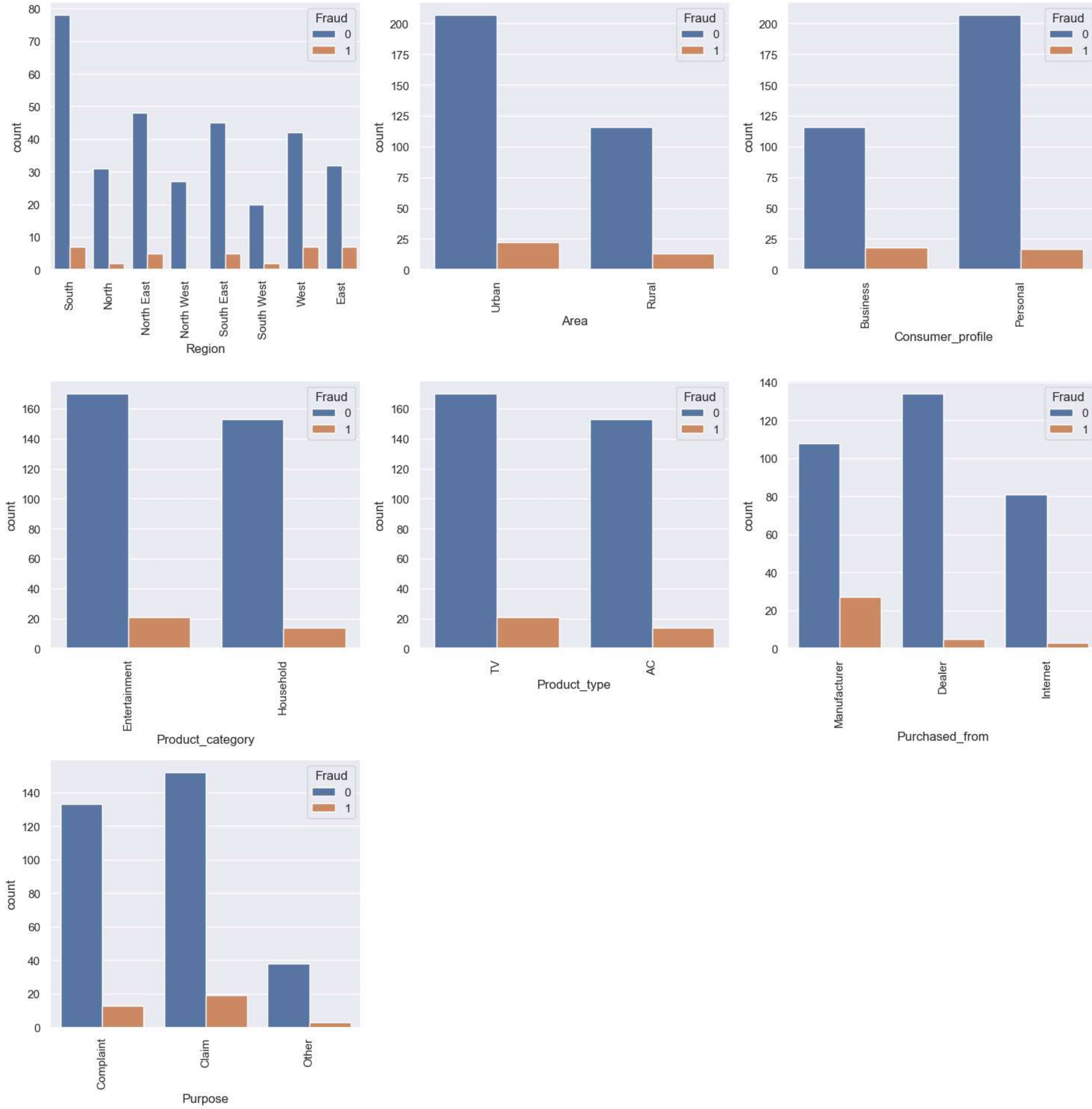
Issue	AC_1003_Issue	TV_2001_Issue	TV_2002_Issue	TV_2003_Issue	Claim_Value	Service_Centre	Product_Age	Purchased_from	Call_details	Pur
0	0	1	2	0	15000.0	10	60	Manufacturer	0.5	Com
1	0	0	0	0	20000.0	12	10	Dealer	1.0	Com
1	2	0	0	0	18000.0	14	10	Dealer	1.4	(
0	0	1	1	0	12000.0	16	20	Manufacturer	2.0	Com
0	0	0	1	2	25000.0	15	6	Dealer	1.3	(

In [5]:
```
#Check the number of unique value from all of the object datatype
df.select_dtypes(include='object').nunique()
```

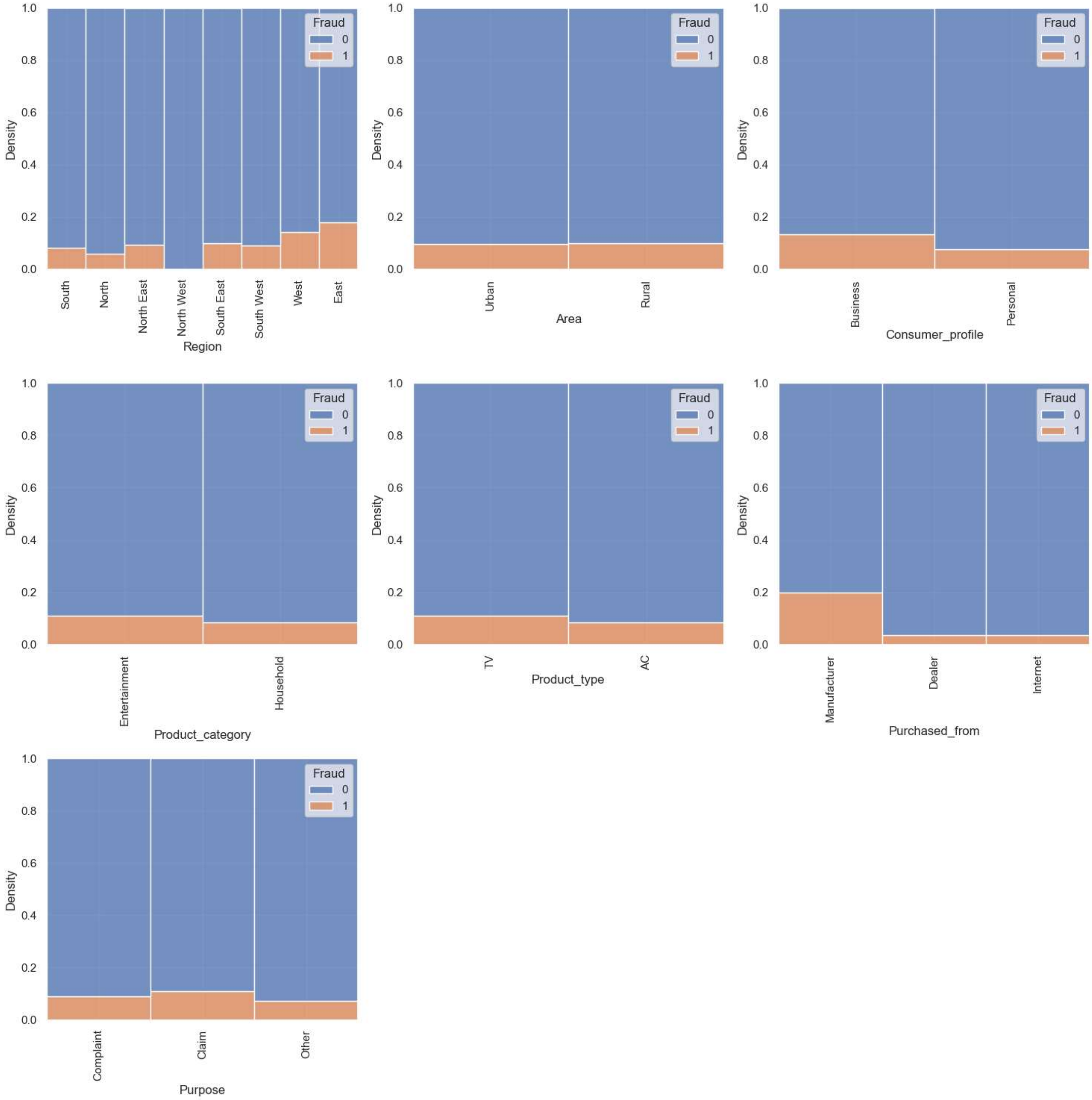
Out[5]:
```
Region              8
Area                2
Consumer_profile    2
Product_category    2
Product_type        2
Purchased_from      3
Purpose             3
dtype: int64
```

Exploratory Data Analysis

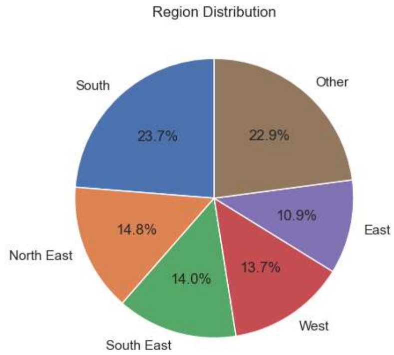
In [7]:
```
# list of categorical variables to plot
cat_vars = ['Region', 'Area', 'Consumer_profile',
            'Product_category', 'Product_type', 'Purchased_from',
            'Purpose']

# create figure with subplots
fig, axs = plt.subplots(nrows=3, ncols=3, figsize=(15, 15))
axs = axs.flatten()

# create barplot for each categorical variable
for i, var in enumerate(cat_vars):
    sns.countplot(x=var, hue='Fraud', data=df, ax=axs[i])
    axs[i].set_xticklabels(axs[i].get_xticklabels(), rotation=90)

# adjust spacing between subplots
fig.tight_layout()

# remove the eigth subplot
fig.delaxes(axs[7])

# remove the ninth subplot
fig.delaxes(axs[8])

# show plot
plt.show()
```

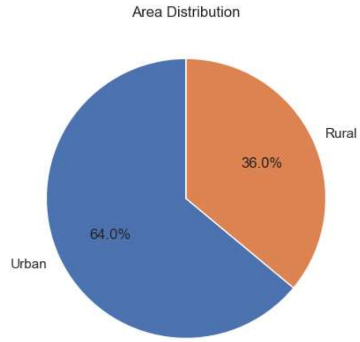

Fraud
0
1
count
South
North
North East
North West
South East
South West
West
East
Region
Urban
Rural
Area
Business
Personal
Consumer_profile
Entertainment
Household
Product_category
TV
AC
Product_type
Manufacturer
Dealer
Internet
Purchased_from
Complaint
Claim
Other
Purpose

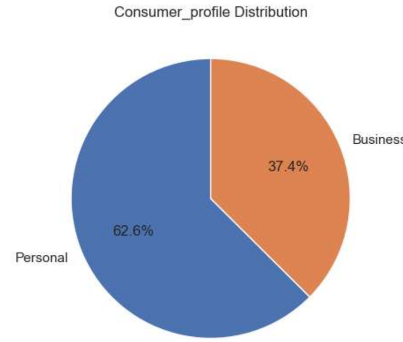
In [8]:
```
import warnings
warnings.filterwarnings("ignore")
# get list of categorical variables
cat_vars = ['Region', 'Area', 'Consumer_profile',
            'Product_category', 'Product_type', 'Purchased_from',
            'Purpose']

# create figure with subplots
fig, axs = plt.subplots(nrows=3, ncols=3, figsize=(15, 15))
axs = axs.flatten()

# create histplot for each categorical variable
for i, var in enumerate(cat_vars):
    sns.histplot(x=var, hue='Fraud', data=df, ax=axs[i], multiple="fill", kde=False, element="bars", fill=True, stat='
    axs[i].set_xticklabels(df[var].unique(), rotation=90)
    axs[i].set_xlabel(var)

# adjust spacing between subplots
fig.tight_layout()

# remove the eigth subplot
fig.delaxes(axs[7])

# remove the ninth subplot
fig.delaxes(axs[8])

# show plot
plt.show()
```

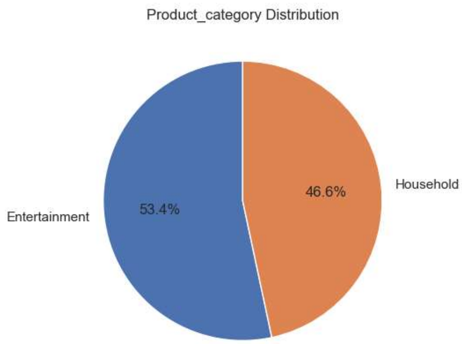

Fraud
0
1
Density
1.0
0.8
0.6
0.4
0.2
0.0
South
North
North East
North West
South East
South West
West
East
Region
Urban
Rural
Area
Business
Personal
Consumer_profile
Entertainment
Household
Product_category
TV
AC
Product_type
Manufacturer
Dealer
Internet
Purchased_from
Complaint
Claim
Other
Purpose

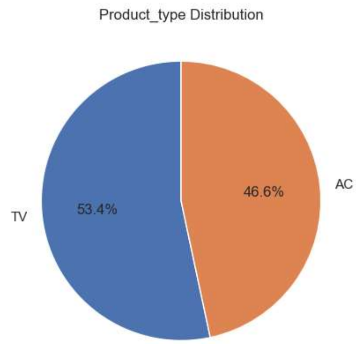
In [9]:
```
# Specify the maximum number of categories to show individually
max_categories = 5

cat_vars = ['Region', 'Area', 'Consumer_profile',
            'Product_category', 'Product_type', 'Purchased_from',
            'Purpose']

# Create a figure and axes
fig, axs = plt.subplots(nrows=3, ncols=3, figsize=(15, 15))

# Create a pie chart for each categorical variable
for i, var in enumerate(cat_vars):
    if i < len(axs.flat):
        # Count the number of occurrences for each category
        cat_counts = df[var].value_counts()

        # Group categories beyond the top max_categories as 'Other'
        if len(cat_counts) > max_categories:
            cat_counts_top = cat_counts[:max_categories]
            cat_counts_other = pd.Series(cat_counts[max_categories:].sum(), index=['Other'])
            cat_counts = cat_counts_top.append(cat_counts_other)

        # Create a pie chart
        axs.flat[i].pie(cat_counts, labels=cat_counts.index, autopct='%1.1f%%', startangle=90)

        # Set a title for each subplot
        axs.flat[i].set_title(f'{var} Distribution')

# Adjust spacing between subplots
fig.tight_layout()

# remove eigth plot
fig.delaxes(axs[2][1])

# remove ninth plot
fig.delaxes(axs[2][2])

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

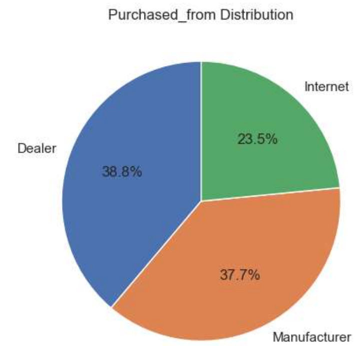

Region Distribution
South
23.7%
Other
22.9%
North East
14.8%
10.9%
East
14.0%
13.7%
West
South East

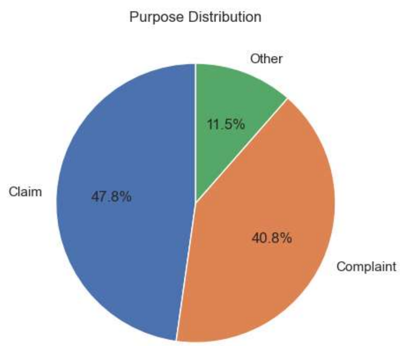

Area Distribution
Rural
36.0%
Urban
64.0%


Consumer_profile Distribution
Business
37.4%
Personal
62.6%

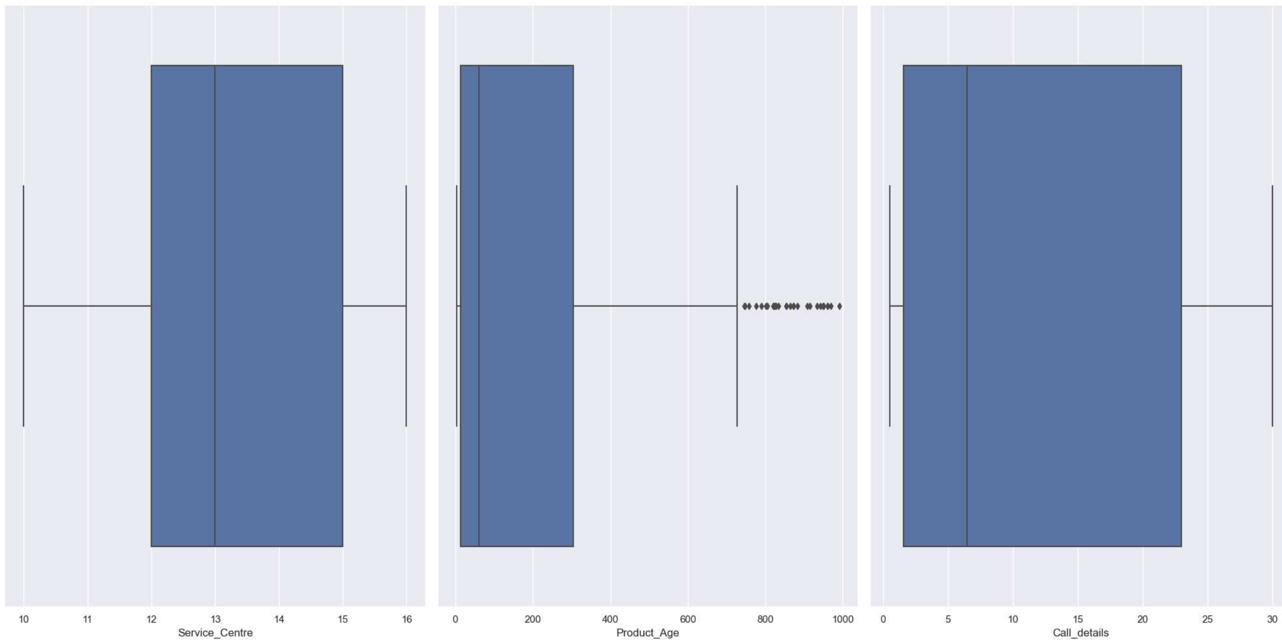

Product_category Distribution
Household
46.6%
Entertainment
53.4%


Product_type Distribution
AC
46.6%
TV
53.4%

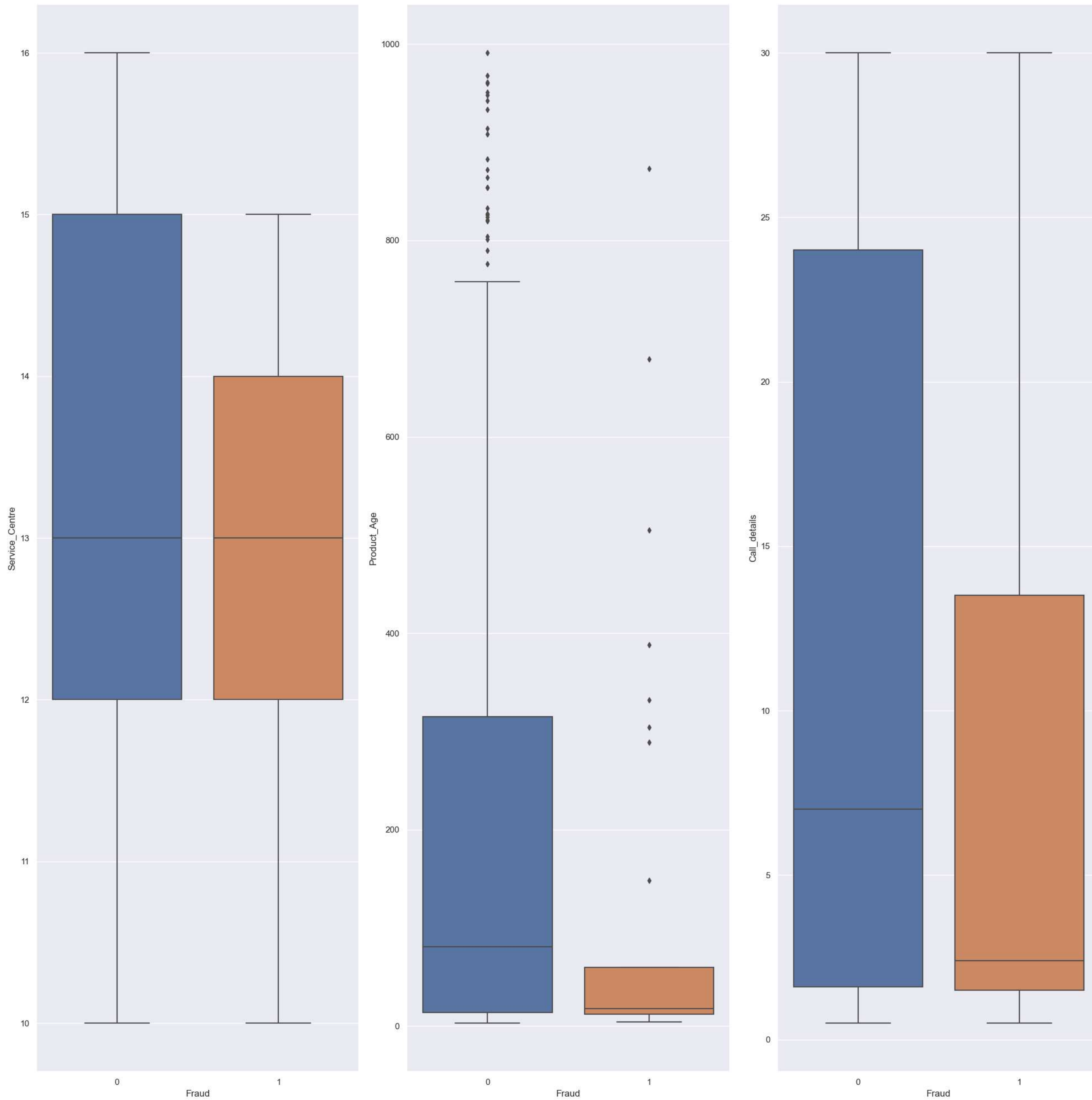

Purchased_from Distribution
Internet
23.5%
Dealer
38.8%
37.7%
Manufacturer


Purpose Distribution
Other
11.5%
Claim
47.8%
40.8%
Complaint

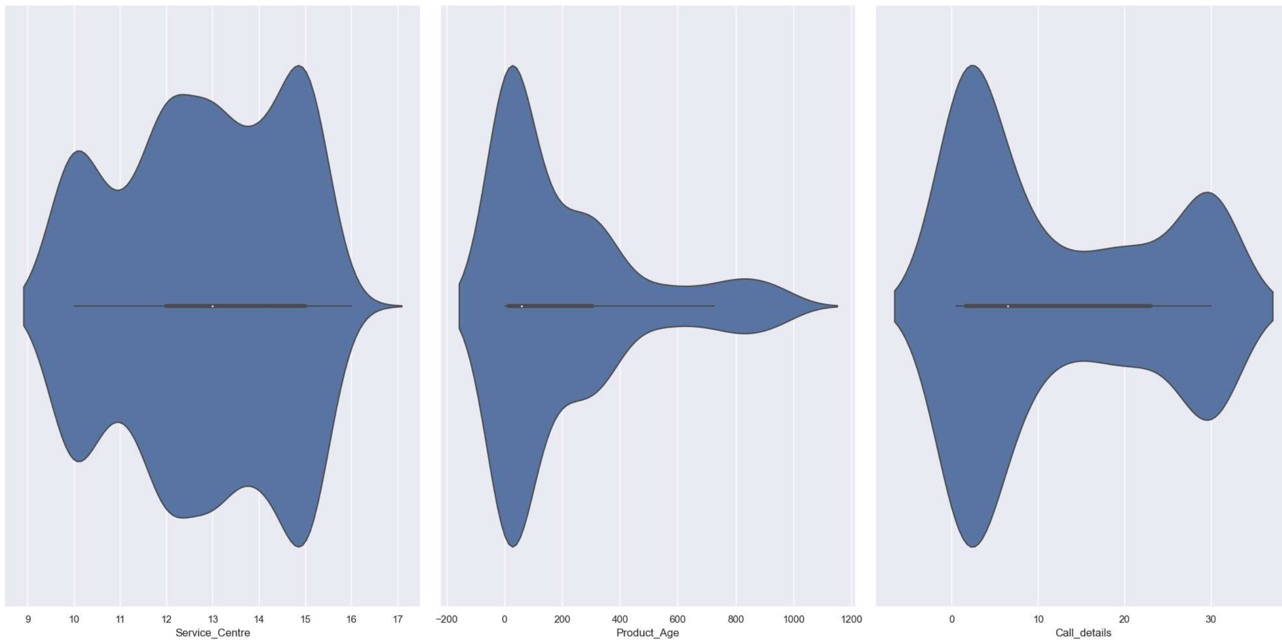
In [10]:
```
num_vars = ['Service_Centre', 'Product_Age','Call_details']

fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(20, 10))
axs = axs.flatten()

for i, var in enumerate(num_vars):
    sns.boxplot(x=var, data=df, ax=axs[i])

fig.tight_layout()

plt.show()
```



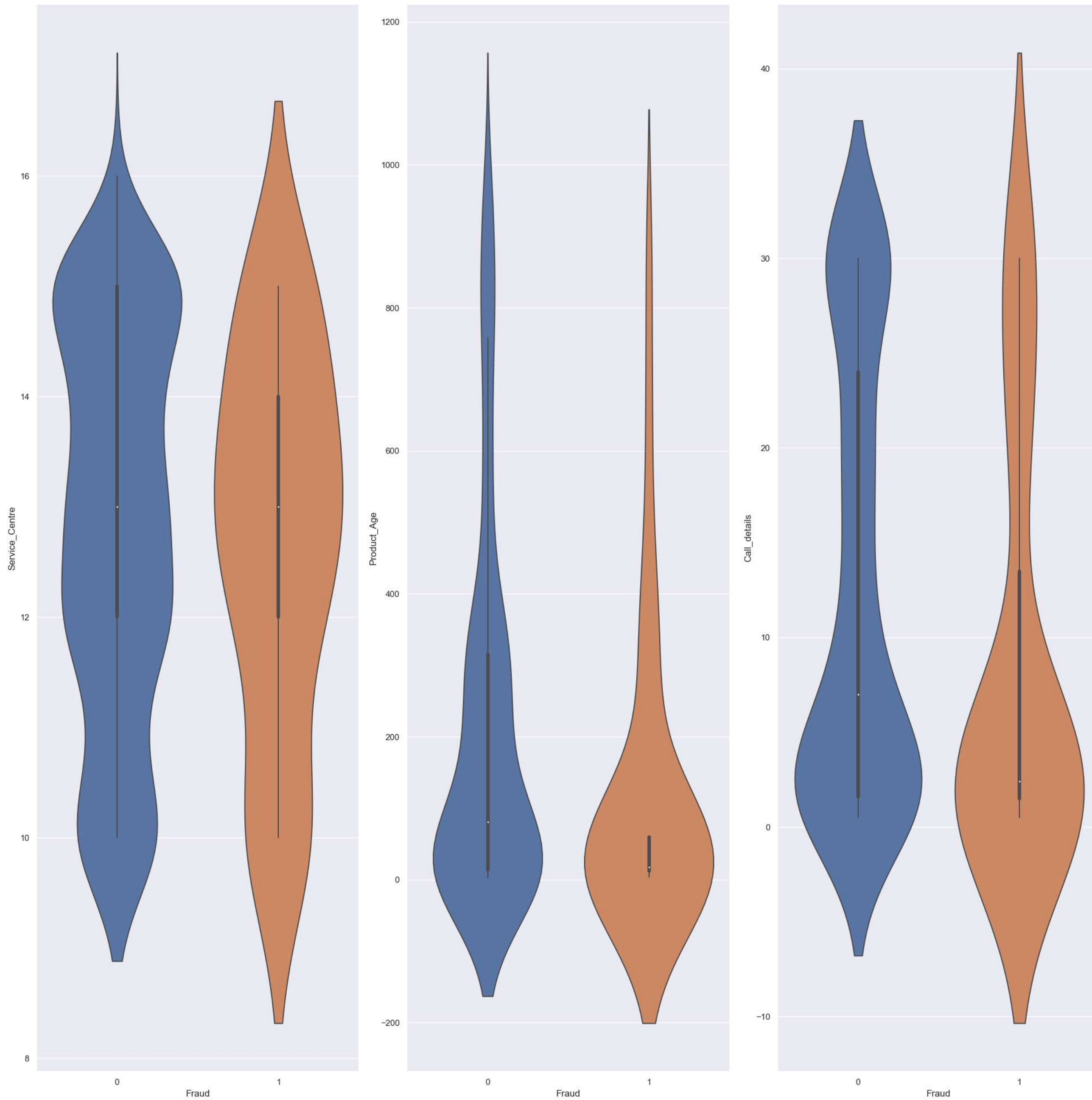
In [12]:
```
num_vars = ['Service_Centre', 'Product_Age','Call_details']

fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(20, 20))
axs = axs.flatten()

for i, var in enumerate(num_vars):
    sns.boxplot(y=var, x='Fraud', data=df, ax=axs[i])

fig.tight_layout()

plt.show()
```



In [13]:
```
num_vars = ['Service_Centre', 'Product_Age','Call_details']

fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(20, 10))
axs = axs.flatten()

for i, var in enumerate(num_vars):
    sns.violinplot(x=var, data=df, ax=axs[i])

fig.tight_layout()

plt.show()
```



In [15]:
```
num_vars = ['Service_Centre', 'Product_Age','Call_details']

fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(20, 20))
axs = axs.flatten()

for i, var in enumerate(num_vars):
    sns.violinplot(y=var, data=df, x='Fraud', ax=axs[i])

fig.tight_layout()

plt.show()
```



Data Preprocessing Part 2

In [16]:
```
#Check missing value
check_missing = df.isnull().sum() * 100 / df.shape[0]
check_missing[check_missing > 0].sort_values(ascending=False)
```

Out[16]:
```
Series([], dtype: float64)
```

Label Encoding for each Object datatype

In [17]:
```
# Loop over each column in the DataFrame where dtype is 'object'
for col in df.select_dtypes(include=['object']).columns:

    # Print the column name and the unique values
    print(f"{col}: {df[col].unique()}")
```

```
Region: ['South' 'North' 'North East' 'North West' 'South East' 'South West'
 'West' 'East']
Area: ['Urban' 'Rural']
Consumer_profile: ['Business' 'Personal']
Product_category: ['Entertainment' 'Household']
Product_type: ['TV' 'AC']
Purchased_from: ['Manufacturer' 'Dealer' 'Internet']
Purpose: ['Complaint' 'Claim' 'Other']
```

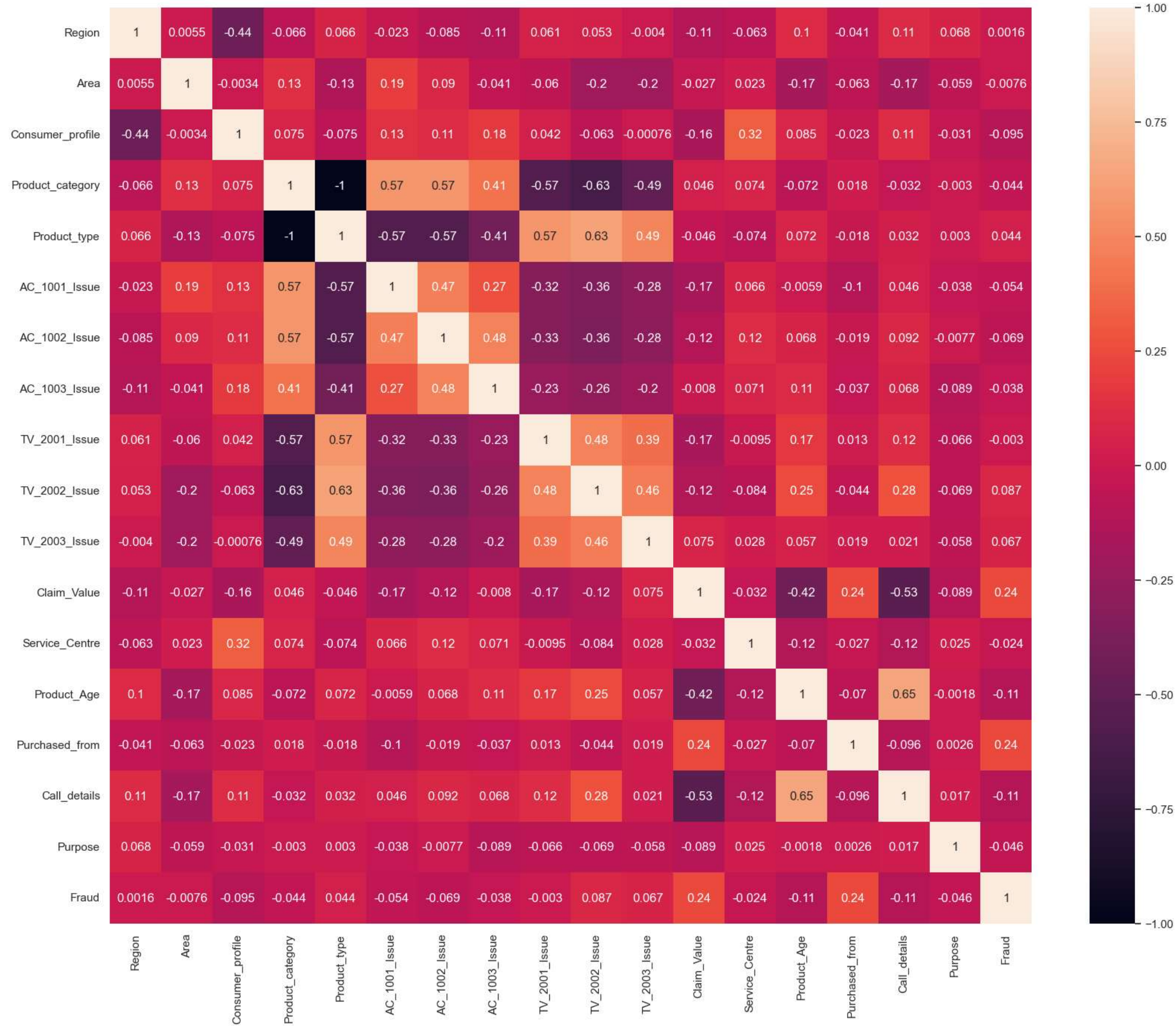
In [18]:
```
from sklearn import preprocessing

# Loop over each column in the DataFrame where dtype is 'object'
for col in df.select_dtypes(include=['object']).columns:

    # Initialize a LabelEncoder object
    label_encoder = preprocessing.LabelEncoder()

    # Fit the encoder to the unique values in the column
    label_encoder.fit(df[col].unique())

    # Transform the column using the encoder
    df[col] = label_encoder.transform(df[col])

    # Print the column name and the unique encoded values
    print(f"{col}: {df[col].unique()}")
```

```
Region: [4 1 2 3 5 6 7 0]
Area: [1 0]
Consumer_profile: [0 1]
Product_category: [0 1]
Product_type: [1 0]
Purchased_from: [2 0 1]
Purpose: [1 0 2]
```

Correlation Heatmap

In [19]:
```python
#Correlation Heatmap (print the correlation score each variables)
plt.figure(figsize=(20, 16))
sns.heatmap(df.corr(), fmt='.2g', annot=True)
```

Out[19]: `<AxesSubplot:>`



Train Test Split

In [20]:
```python
from sklearn.model_selection import train_test_split
# Select the features (X) and the target variable (y)
X = df.drop('Fraud', axis=1)
y = df['Fraud']

# Split the 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=0)
```

Remove the Outlier from train data using Z-Score

In [22]:
```
from scipy import stats

# Define the columns for which you want to remove outliers
selected_columns = ['Service_Centre', 'Product_Age','Call_details']

# Calculate the Z-scores for the selected columns in the training data
z_scores = np.abs(stats.zscore(X_train[selected_columns]))

# Set a threshold value for outlier detection (e.g., 3)
threshold = 3

# Find the indices of outliers based on the threshold
outlier_indices = np.where(z_scores > threshold)[0]

# Remove the outliers from the training data
X_train = X_train.drop(X_train.index[outlier_indices])
y_train = y_train.drop(y_train.index[outlier_indices])
```

Decision Tree

In [23]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
dtree = DecisionTreeClassifier(class_weight='balanced')
param_grid = {
    'max_depth': [3, 4, 5, 6, 7, 8],
    'min_samples_split': [2, 3, 4],
    'min_samples_leaf': [1, 2, 3, 4],
    'random_state': [0, 42]
}

# Perform a grid search with cross-validation to find the best hyperparameters
grid_search = GridSearchCV(dtree, param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print(grid_search.best_params_)
```

```
{'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_split': 2, 'random_state': 0}
```

In [24]:
```
from sklearn.tree import DecisionTreeClassifier
dtree = DecisionTreeClassifier(random_state=0, max_depth=8, min_samples_leaf=1, min_samples_split=2, class_weight='bal
dtree.fit(X_train, y_train)
```

Out[24]:
```
DecisionTreeClassifier(class_weight='balanced', max_depth=8, random_state=0)
```

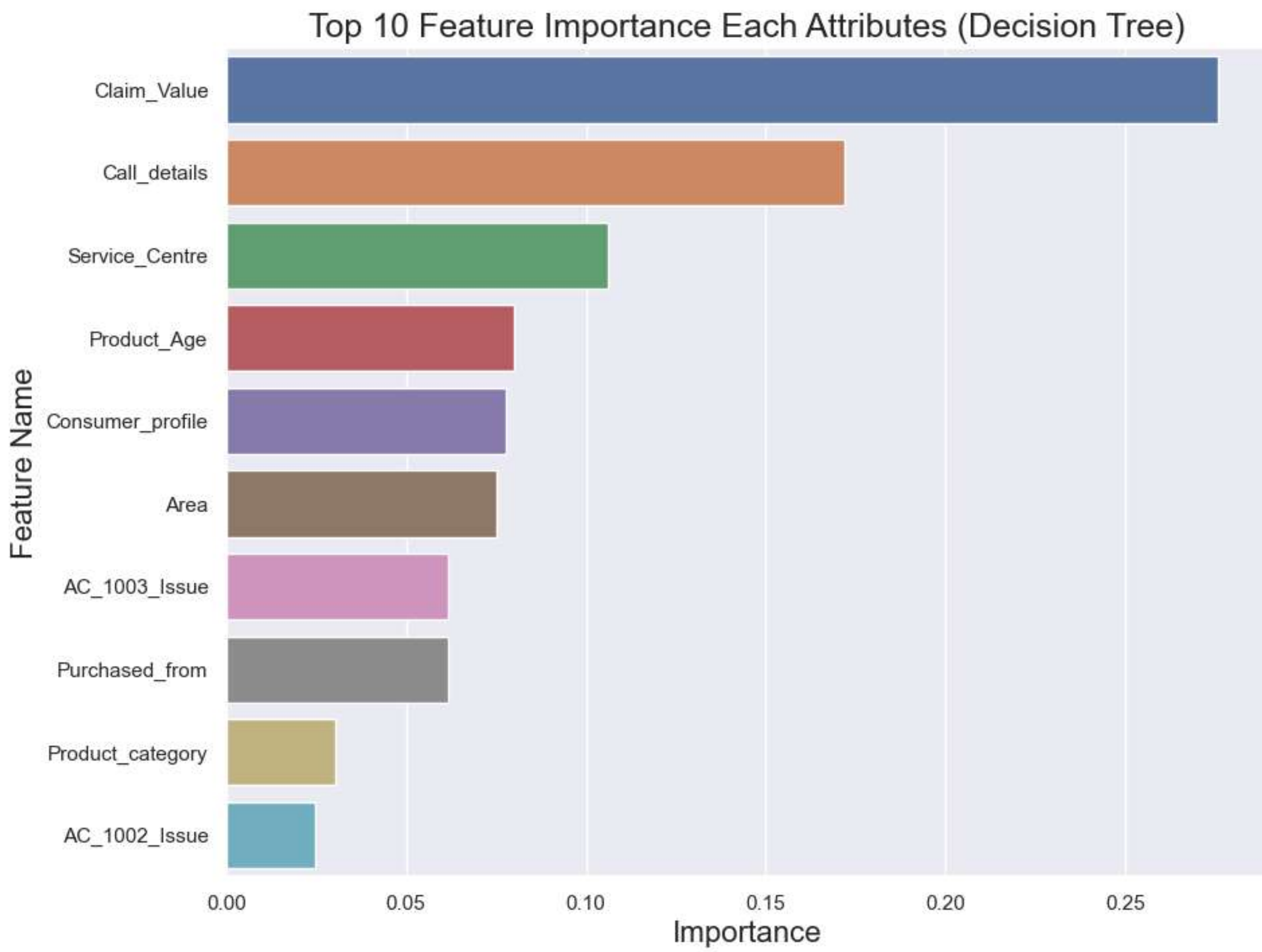
In [25]:
```
from sklearn.metrics import accuracy_score
y_pred = dtree.predict(X_test)
print("Accuracy Score :", round(accuracy_score(y_test, y_pred)*100 ,2), "%")
```

```
Accuracy Score : 84.72 %
```

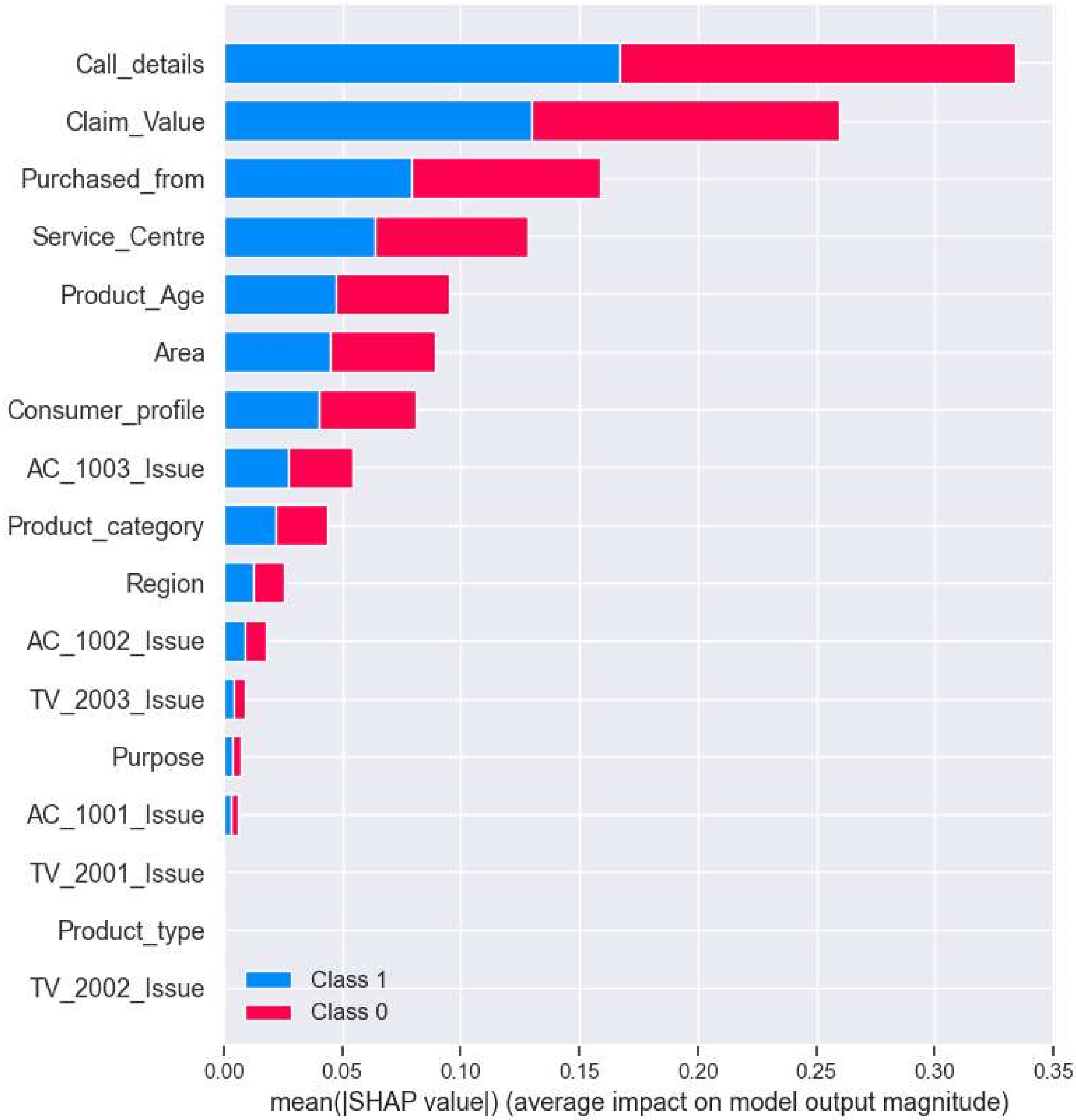
In [26]:
```
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score, jaccard_score, log_loss
print('F-1 Score : ',(f1_score(y_test, y_pred, average='micro')))
print('Precision Score : ',(precision_score(y_test, y_pred, average='micro')))
print('Recall Score : ',(recall_score(y_test, y_pred, average='micro')))
print('Jaccard Score : ',(jaccard_score(y_test, y_pred, average='micro')))
print('Log Loss : ',(log_loss(y_test, y_pred)))
```

```
F-1 Score :  0.8472222222222222
Precision Score :  0.8472222222222222
Recall Score :  0.8472222222222222
Jaccard Score :  0.7349397590361446
Log Loss :  5.276846348936932
```

In [27]:
```
imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": dtree.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

fi2 = fi.head(10)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Top 10 Feature Importance Each Attributes (Decision Tree)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```

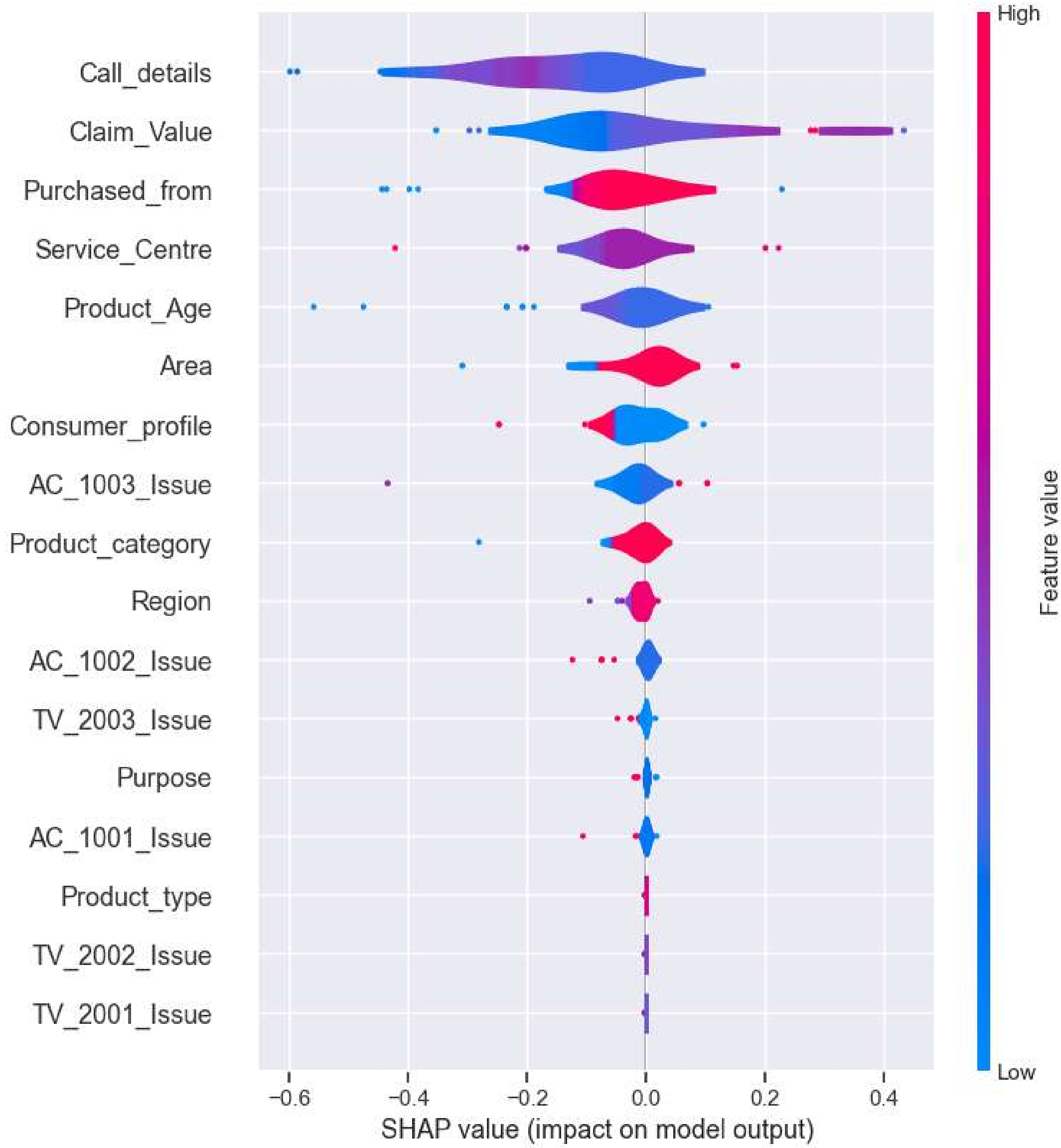


In [28]:
```
import shap
explainer = shap.TreeExplainer(dtree)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values, X_test)
```



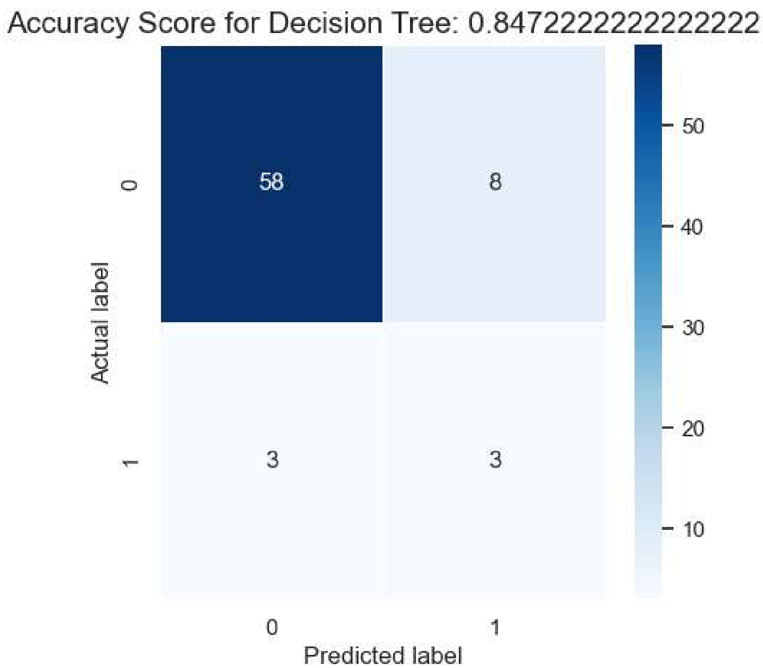
In [29]:
```
# compute SHAP values
explainer = shap.TreeExplainer(dtree)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values[1], X_test.values, feature_names = X_test.columns)
```

In [30]:
```
# compute SHAP values
explainer = shap.TreeExplainer(dtree)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values[1], X_test.values, feature_names = X_test.columns, plot_type="violin")
```



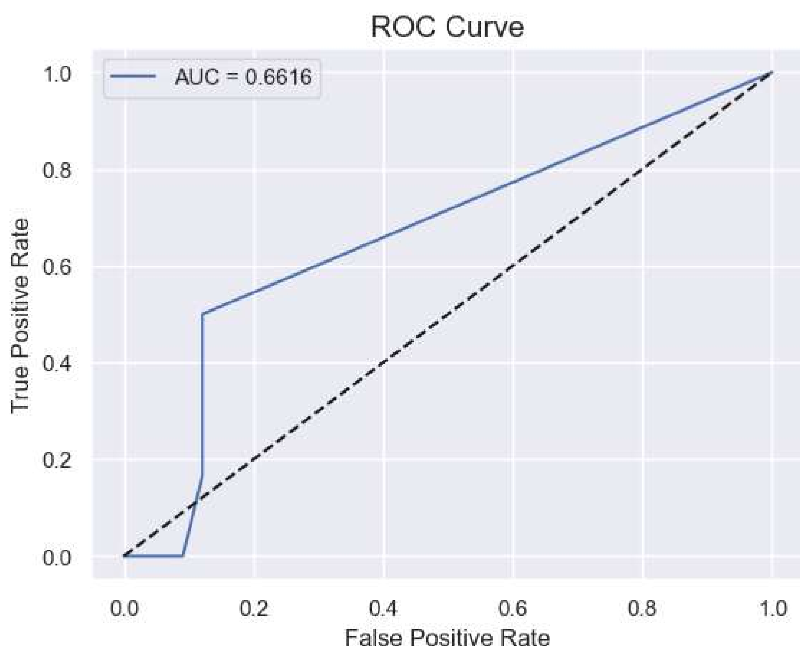
In [31]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(5,5))
sns.heatmap(data=cm,linewidths=.5, annot=True,  cmap = 'Blues')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
all_sample_title = 'Accuracy Score for Decision Tree: {0}'.format(dtree.score(X_test, y_test))
plt.title(all_sample_title, size = 15)
```

Out[31]:
```
Text(0.5, 1.0, 'Accuracy Score for Decision Tree: 0.8472222222222222')
```



In [32]:
```
from sklearn.metrics import roc_curve, roc_auc_score
y_pred_proba = dtree.predict_proba(X_test)[:][:,1]

df_actual_predicted = pd.concat([pd.DataFrame(np.array(y_test), columns=['y_actual']), pd.DataFrame(y_pred_proba, colu
df_actual_predicted.index = y_test.index

fpr, tpr, tr = roc_curve(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])
auc = roc_auc_score(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])

plt.plot(fpr, tpr, label='AUC = %0.4f' %auc)
plt.plot(fpr, fpr, linestyle = '--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve', size = 15)
plt.legend()
```

Out[32]:
```
<matplotlib.legend.Legend at 0x235e5420070>
```



Random Forest

In [33]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
rfc = RandomForestClassifier(class_weight='balanced')
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [None, 5, 10],
    'max_features': ['sqrt', 'log2', None],
    'random_state': [0, 42]
}

# Perform a grid search with cross-validation to find the best hyperparameters
grid_search = GridSearchCV(rfc, param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print(grid_search.best_params_)
```

```
{'max_depth': 10, 'max_features': 'sqrt', 'n_estimators': 100, 'random_state': 42}
```

In [34]:
```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(random_state=42, max_features='sqrt', n_estimators=100, max_depth=10, class_weight='balan
rfc.fit(X_train, y_train)
```

Out[34]:
```
RandomForestClassifier(class_weight='balanced', max_depth=10,
                       max_features='sqrt', random_state=42)
```

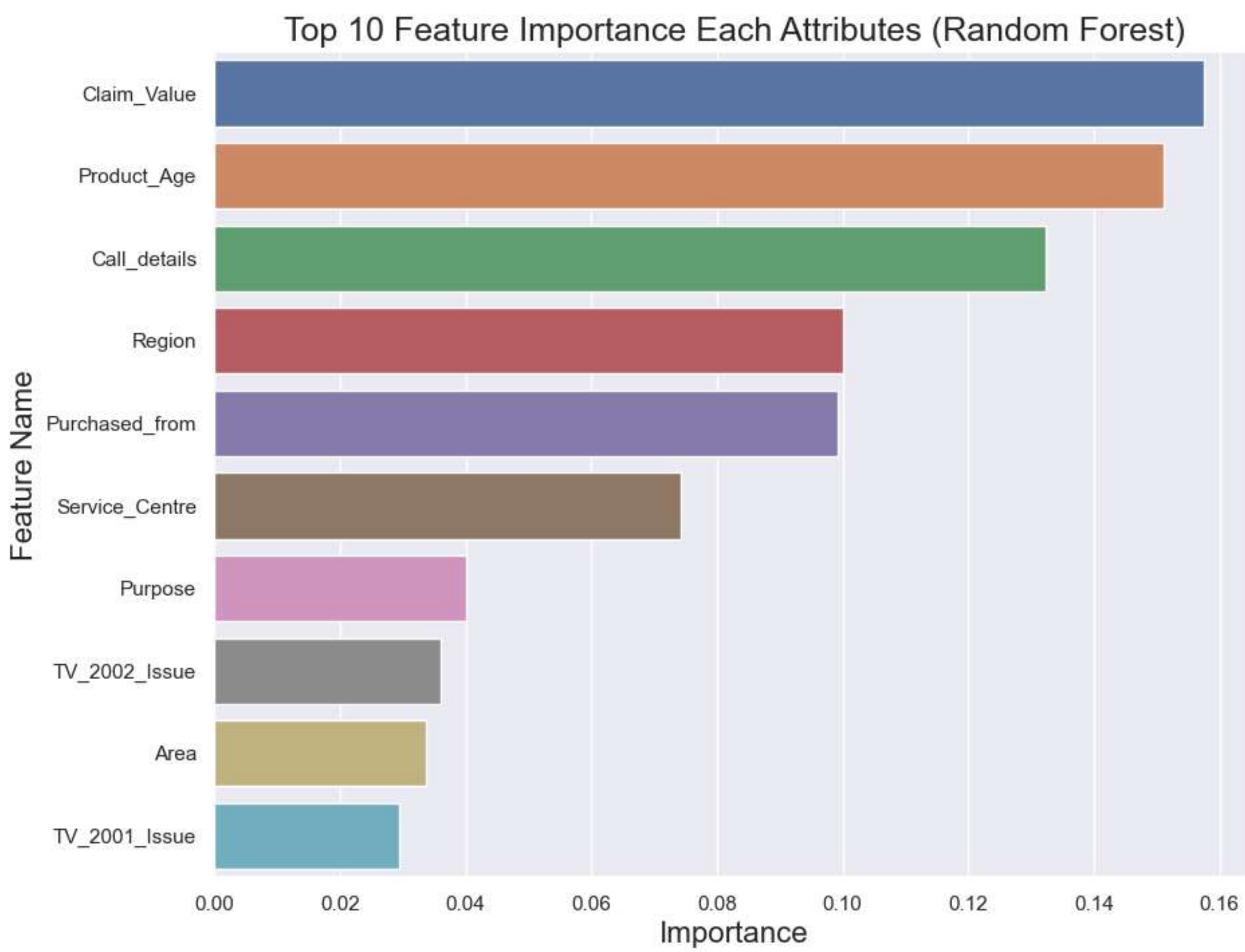
In [35]:
```
y_pred = rfc.predict(X_test)
print("Accuracy Score :", round(accuracy_score(y_test, y_pred)*100 ,2), "%")
```

```
Accuracy Score : 91.67 %
```

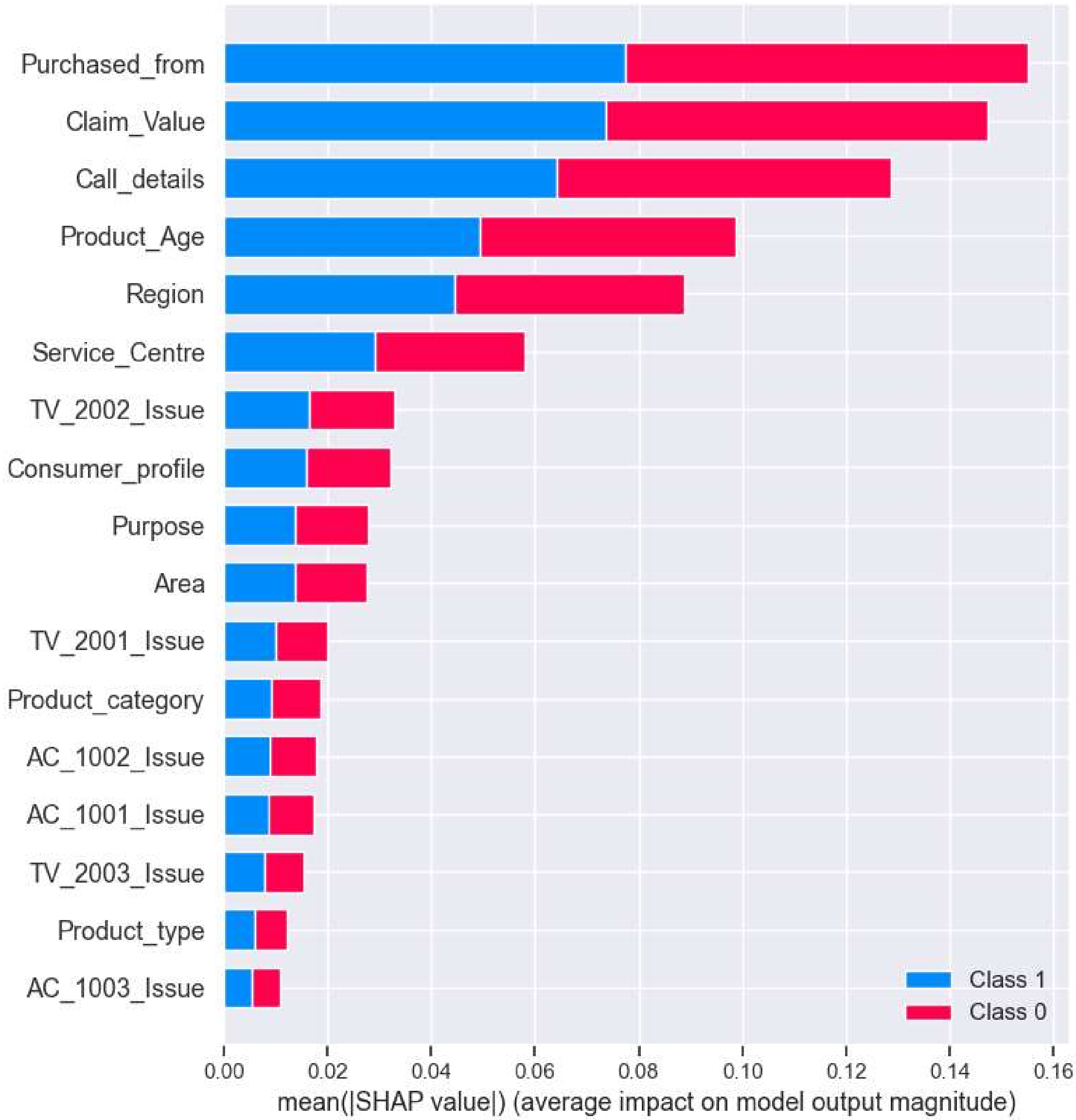
In [36]:
```
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score, jaccard_score, log_loss
print('F-1 Score : ',(f1_score(y_test, y_pred, average='micro')))
print('Precision Score : ',(precision_score(y_test, y_pred, average='micro')))
print('Recall Score : ',(recall_score(y_test, y_pred, average='micro')))
print('Jaccard Score : ',(jaccard_score(y_test, y_pred, average='micro')))
print('Log Loss : ',(log_loss(y_test, y_pred)))
```

```
F-1 Score :  0.9166666666666666
Precision Score :  0.9166666666666666
Recall Score :  0.9166666666666666
Jaccard Score :  0.8461538461538461
Log Loss :  2.878253577282285
```

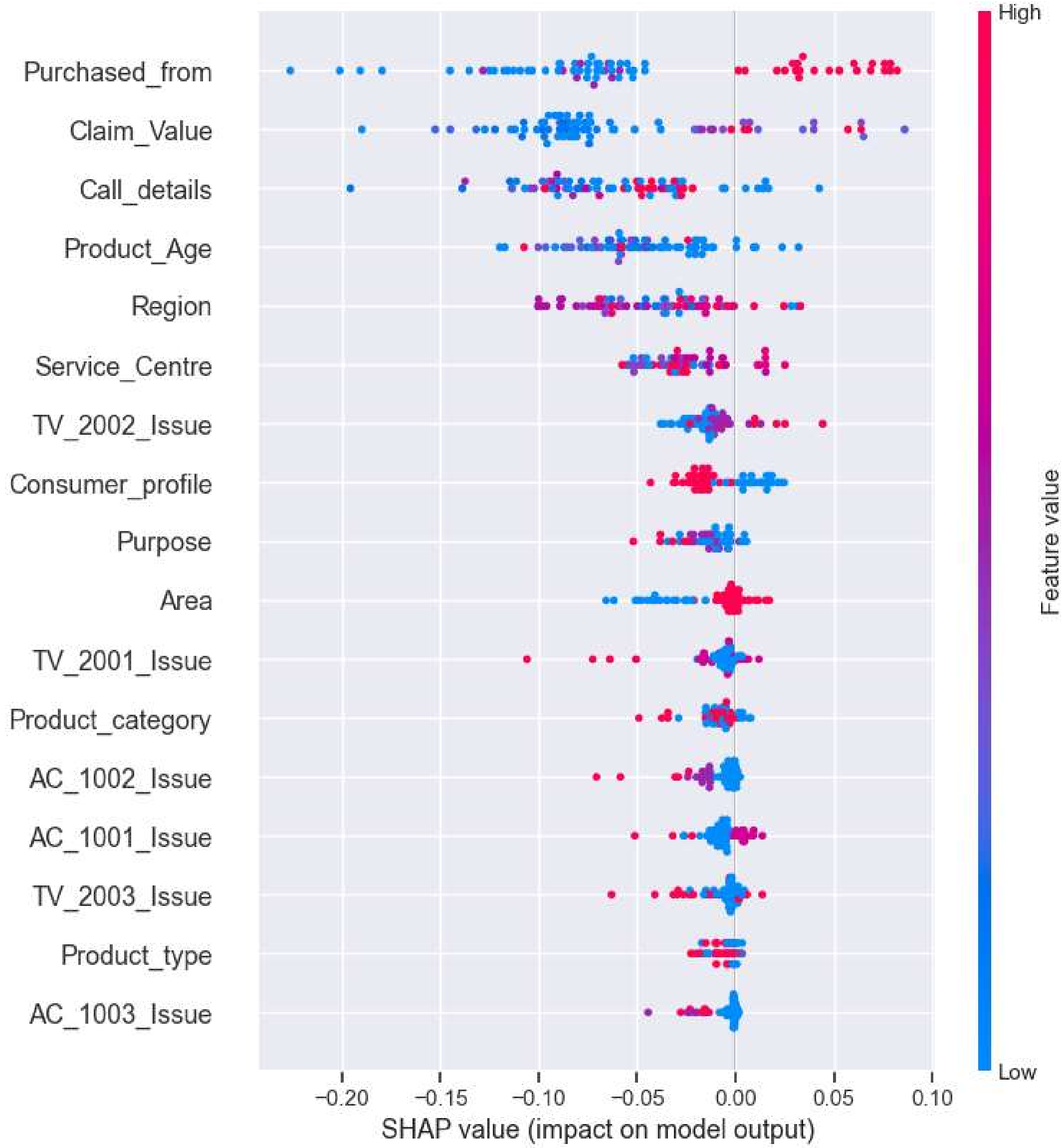
In [37]:
```
imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": rfc.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

fi2 = fi.head(10)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Top 10 Feature Importance Each Attributes (Random Forest)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



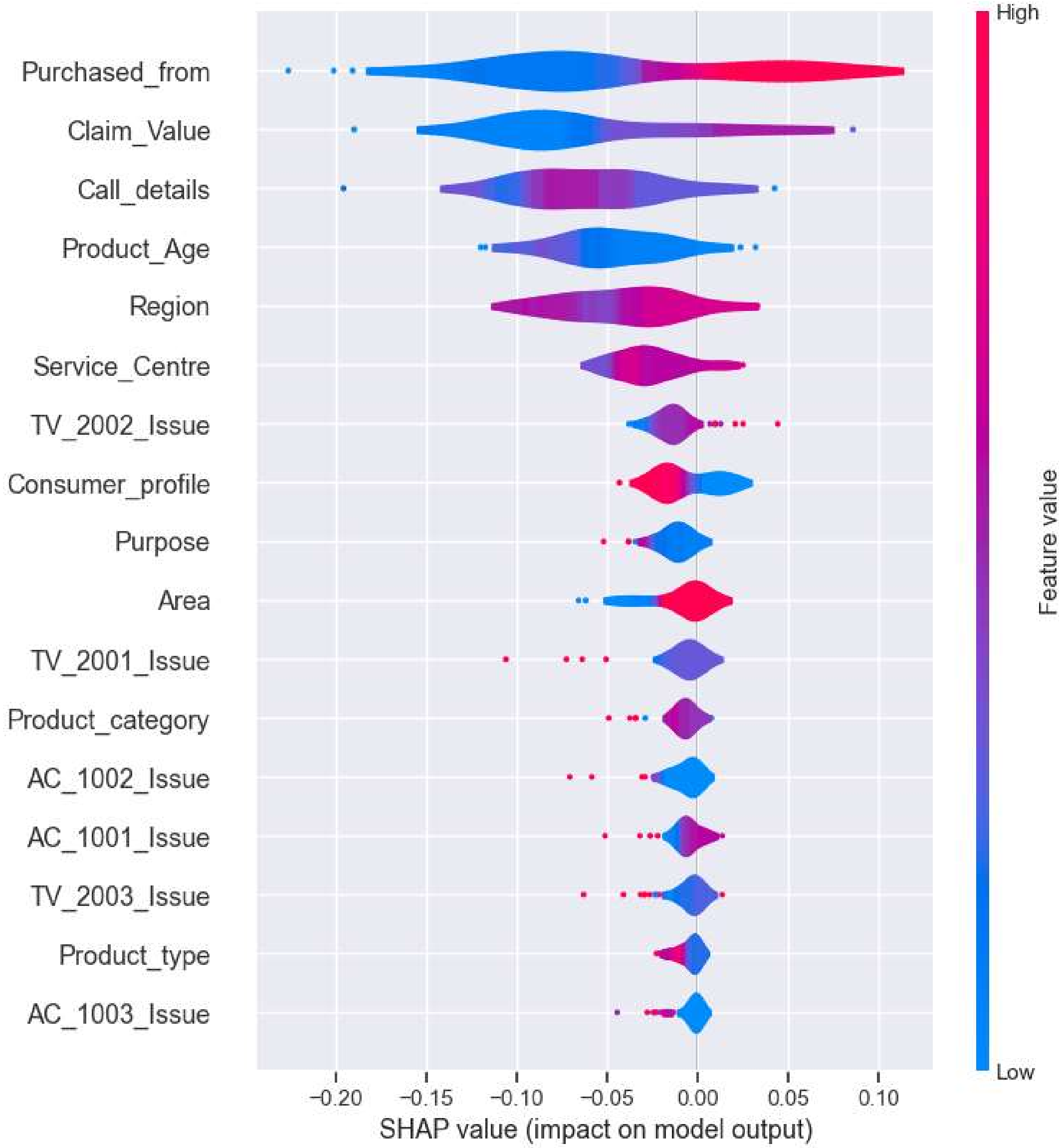
In [38]:
```
import shap
explainer = shap.TreeExplainer(rfc)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values, X_test)
```



In [39]:
```
# compute SHAP values
explainer = shap.TreeExplainer(rfc)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values[1], X_test.values, feature_names = X_test.columns)
```

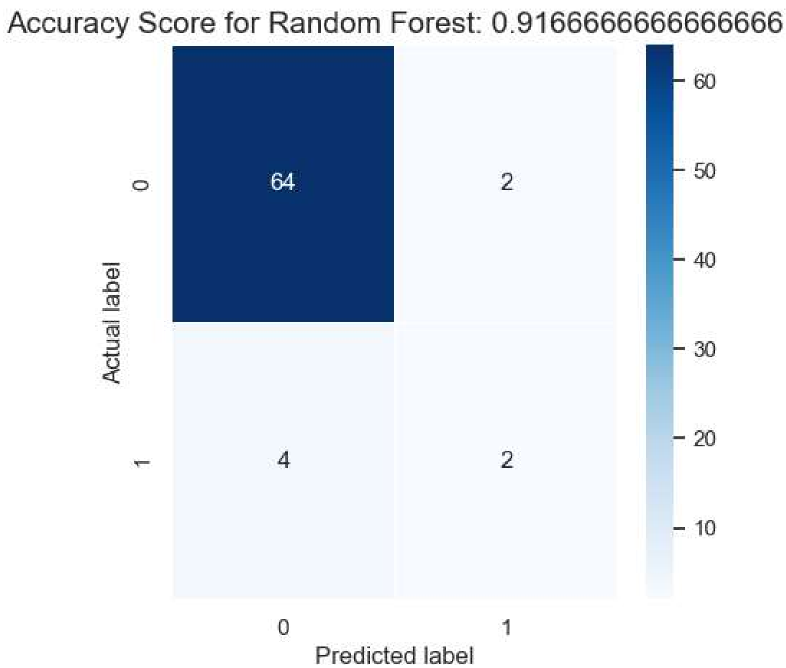


In [40]:
```
# compute SHAP values
explainer = shap.TreeExplainer(rfc)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values[1], X_test.values, feature_names = X_test.columns, plot_type="violin")
```



In [41]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(5,5))
sns.heatmap(data=cm,linewidths=.5, annot=True,  cmap = 'Blues')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
all_sample_title = 'Accuracy Score for Random Forest: {0}'.format(rfc.score(X_test, y_test))
plt.title(all_sample_title, size = 15)
```

Out[41]:
```
Text(0.5, 1.0, 'Accuracy Score for Random Forest: 0.9166666666666666')
```



In [42]:
```
from sklearn.metrics import roc_curve, roc_auc_score
y_pred_proba = rfc.predict_proba(X_test)[:][:,1]

df_actual_predicted = pd.concat([pd.DataFrame(np.array(y_test), columns=['y_actual']), pd.DataFrame(y_pred_proba, colu
df_actual_predicted.index = y_test.index

fpr, tpr, tr = roc_curve(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])
auc = roc_auc_score(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])

plt.plot(fpr, tpr, label='AUC = %0.4f' %auc)
plt.plot(fpr, fpr, linestyle = '--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve', size = 15)
plt.legend()
```

Out[42]: <matplotlib.legend.Legend at 0x235e63cfac0>