In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, accura
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import GridSearchCV
```

In [2]:
```
# Load the dataset
data = "C:/Users/asus/OneDrive/Documents/Assignments/SEM-2/ADSC_2910_Integr
space_data = pd.read_csv(data)
# Check for missing values in the dataset
missing_values = space_data.isnull().sum()
missing_values[missing_values > 0]
```

Out[2]:
```
OBJECT_ID          39
RCS_SIZE          198
COUNTRY_CODE       39
LAUNCH_DATE        39
SITE               39
DECAY_DATE      14372
dtype: int64
```

In [3]:
```
space_data.fillna(method='ffill', inplace=True)
space_data.isnull().sum()
```

Out[3]:
```
CCSDS_OMM_VERS              0
COMMENT                     0
CREATION_DATE               0
ORIGINATOR                  0
OBJECT_NAME                 0
OBJECT_ID                   0
CENTER_NAME                 0
REF_FRAME                   0
TIME_SYSTEM                 0
MEAN_ELEMENT_THEORY         0
EPOCH                       0
MEAN_MOTION                 0
ECCENTRICITY                0
INCLINATION                 0
RA_OF_ASC_NODE              0
ARG_OF_PERICENTER           0
MEAN_ANOMALY                0
EPHEMERIS_TYPE              0
CLASSIFICATION_TYPE         0
NORAD_CAT_ID                0
ELEMENT_SET_NO              0
REV_AT_EPOCH                0
BSTAR                       0
MEAN_MOTION_DOT             0
MEAN_MOTION_DDOT            0
SEMIMAJOR_AXIS              0
PERIOD                      0
APOAPSIS                    0
PERIAPSIS                   0
OBJECT_TYPE                 0
RCS_SIZE                    0
COUNTRY_CODE                0
LAUNCH_DATE                 0
SITE                        0
DECAY_DATE              14372
FILE                        0
GP_ID                       0
TLE_LINE0                   0
TLE_LINE1                   0
TLE_LINE2                   0
dtype: int64
```

In [4]:

```
selected_columns = ['MEAN_MOTION', 'ECCENTRICITY', 'INCLINATION', 'RA_OF_AS
data = space_data[selected_columns]
data
```

Out[4]:

	MEAN_MOTION	ECCENTRICITY	INCLINATION	RA_OF_ASC_NODE	ARG_OF_PERICEN
0	2.921700	0.652893	7.7156	90.2410	243.
1	13.754973	0.003072	82.9193	299.1120	158.
2	1.038224	0.023739	12.1717	16.5368	250.
3	14.775907	0.006062	98.4781	8.7205	37.
4	14.724482	0.006226	98.4232	122.0724	345.
...	...	...	...	...	
14367	15.465781	0.001190	99.0098	214.6827	219.
14368	14.967557	0.005560	99.0272	141.1159	76.
14369	12.909691	0.056673	31.9916	262.9339	162.
14370	14.245319	0.005822	98.6758	348.3068	187.
14371	12.951574	0.002956	90.2762	327.5871	238.

14372 rows × 12 columns

In [5]:
```python
# Initialize the LabelEncoder
encoder = LabelEncoder()

# Fit and transform the 'OBJECT_TYPE' column with LabelEncoder
data['OBJECT_TYPE'] = encoder.fit_transform(data['OBJECT_TYPE'])

# Custom mapping for RCS_SIZE
custom_mapping = {'SMALL': 1, 'MEDIUM': 2, 'LARGE': 3}

# Apply the custom mapping
data['RCS_SIZE'] = data['RCS_SIZE'].map(custom_mapping)

data
```

```
C:\Users\asus\AppData\Local\Temp\ipykernel_12460\3798038054.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  data['OBJECT_TYPE'] = encoder.fit_transform(data['OBJECT_TYPE'])
C:\Users\asus\AppData\Local\Temp\ipykernel_12460\3798038054.py:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  data['RCS_SIZE'] = data['RCS_SIZE'].map(custom_mapping)
```

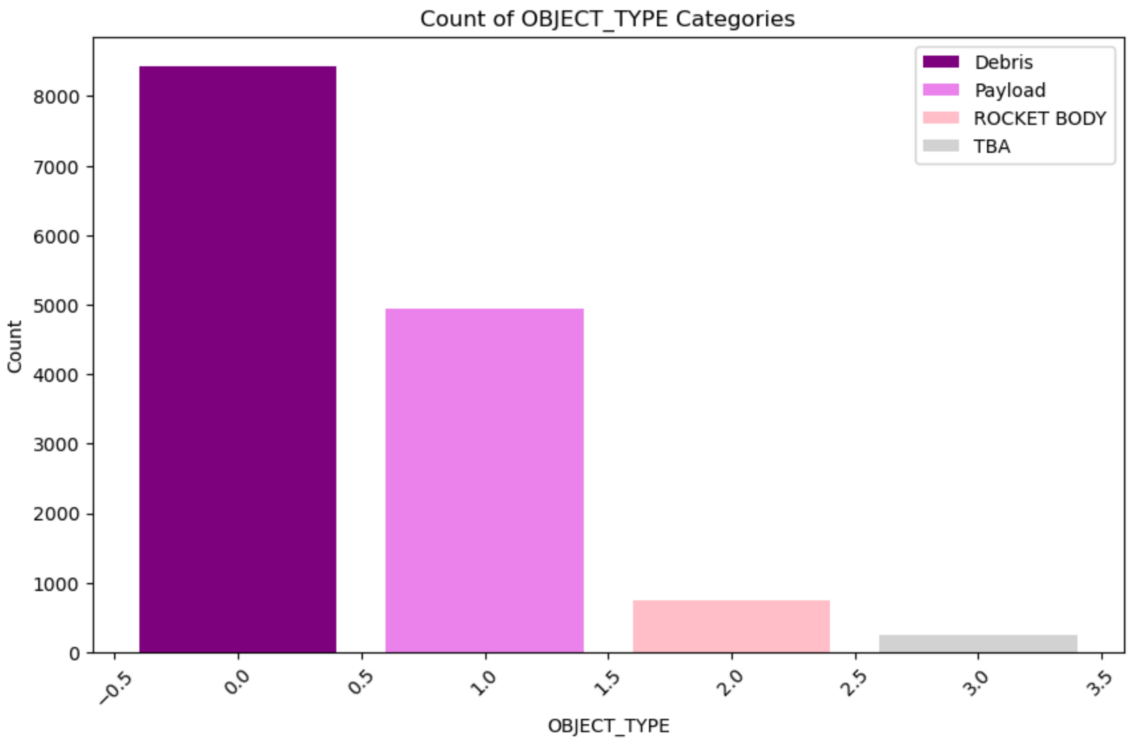
Out[5]:

	MEAN_MOTION	ECCENTRICITY	INCLINATION	RA_OF_ASC_NODE	ARG_OF_PERICEN
0	2.921700	0.652893	7.7156	90.2410	243.
1	13.754973	0.003072	82.9193	299.1120	158.
2	1.038224	0.023739	12.1717	16.5368	250.
3	14.775907	0.006062	98.4781	8.7205	37.
4	14.724482	0.006226	98.4232	122.0724	345.
...	...	...	...	...	
14367	15.465781	0.001190	99.0098	214.6827	219.
14368	14.967557	0.005560	99.0272	141.1159	76.
14369	12.909691	0.056673	31.9916	262.9339	162.
14370	14.245319	0.005822	98.6758	348.3068	187.
14371	12.951574	0.002956	90.2762	327.5871	238.

14372 rows × 12 columns

In [6]:

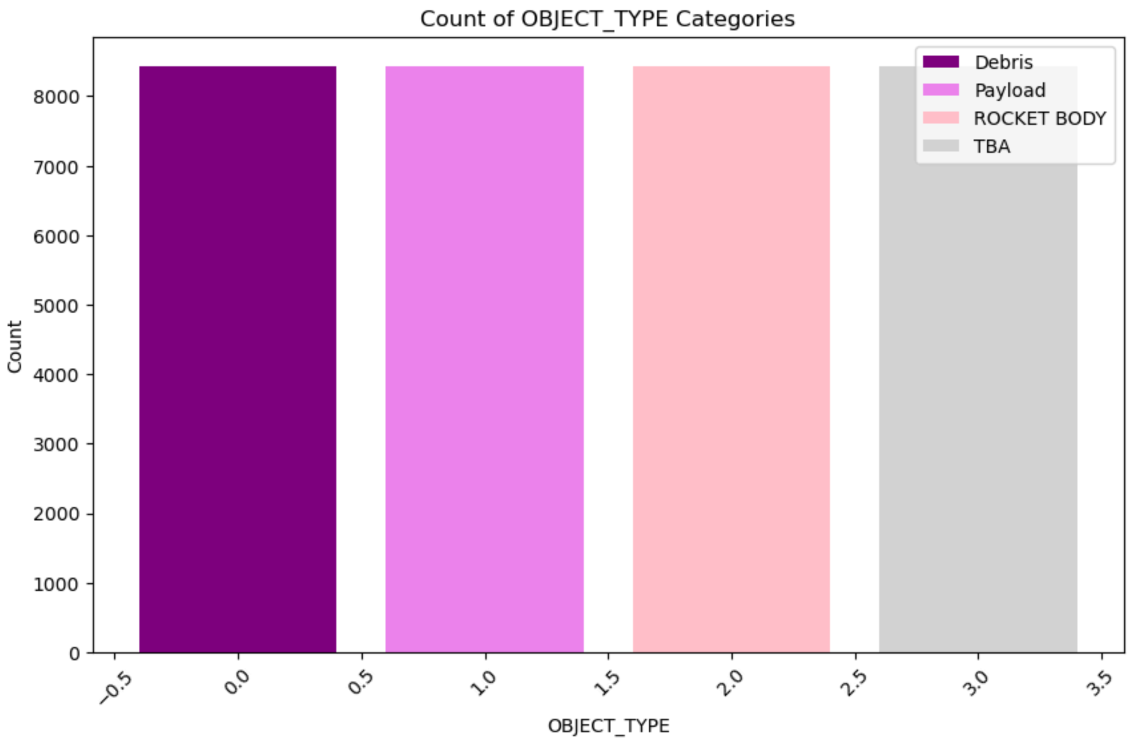
```
# Count the occurrences of each unique value in 'OBJECT_TYPE'
object_counts = data['OBJECT_TYPE'].value_counts()

# Mapping for OBJECT_TYPE to colors and labels for the legend
object_type_mapping = {
    0 : ('Debris', 'purple'),
    1 : ('Payload', 'violet'),
    2 : ('ROCKET BODY', 'pink'),
    3 : ('TBA', 'lightgrey'),
    # Add more mappings if there are more object types
}

# Create the plot
plt.figure(figsize=(10, 6))
bars = []

# Plot each object type count with its specific color
for object_type, count in object_counts.items():
    bar = plt.bar(object_type, count, color=object_type_mapping[object_type
    bars.append(bar)

# Create a custom legend
plt.legend([bar[0] for bar in bars], [object_type_mapping[object_type][0] f

plt.title('Count of OBJECT_TYPE Categories')
plt.xlabel('OBJECT_TYPE')
plt.ylabel('Count')
plt.xticks(rotation=45)

plt.show()
```



In [7]:
```python
# Identify the majority class (DEBRIS, encoded as 0) count
majority_class_count = data['OBJECT_TYPE'].value_counts().max()

# Define the desired sampling strategy: match the majority class count for
sampling_strategy = {0: majority_class_count, 1: majority_class_count, 2: m

# Prepare features and target for SMOTE
X = data.drop('OBJECT_TYPE', axis=1)
y = data['OBJECT_TYPE']

# Apply SMOTE
smote = SMOTE(sampling_strategy=sampling_strategy, random_state=123)
X_resampled, y_resampled = smote.fit_resample(X, y)

# Reconstruct the balanced DataFrame
balanced_data = pd.concat([pd.DataFrame(X_resampled, columns=X.columns),
                           pd.DataFrame(y_resampled, columns=['OBJECT_TYPE'

# Verify the balancing operation
print(balanced_data['OBJECT_TYPE'].value_counts())
```

```
0    8431
1    8431
2    8431
3    8431
Name: OBJECT_TYPE, dtype: int64
```

In [8]:
```
# Count the occurrences of each unique value in 'OBJECT_TYPE'
object_counts = balanced_data['OBJECT_TYPE'].value_counts()

# Mapping for OBJECT_TYPE to colors and labels for the legend
object_type_mapping = {
    0 : ('Debris', 'purple'),
    1 : ('Payload', 'violet'),
    2 : ('ROCKET BODY', 'pink'),
    3 : ('TBA', 'lightgrey'),
    # Add more mappings if there are more object types
}

# Create the plot
plt.figure(figsize=(10, 6))
bars = []

# Plot each object type count with its specific color
for object_type, count in object_counts.items():
    bar = plt.bar(object_type, count, color=object_type_mapping[object_type
    bars.append(bar)

# Create a custom legend
plt.legend([bar[0] for bar in bars], [object_type_mapping[object_type][0] f

plt.title('Count of OBJECT_TYPE Categories')
plt.xlabel('OBJECT_TYPE')
plt.ylabel('Count')
plt.xticks(rotation=45)

plt.show()
```

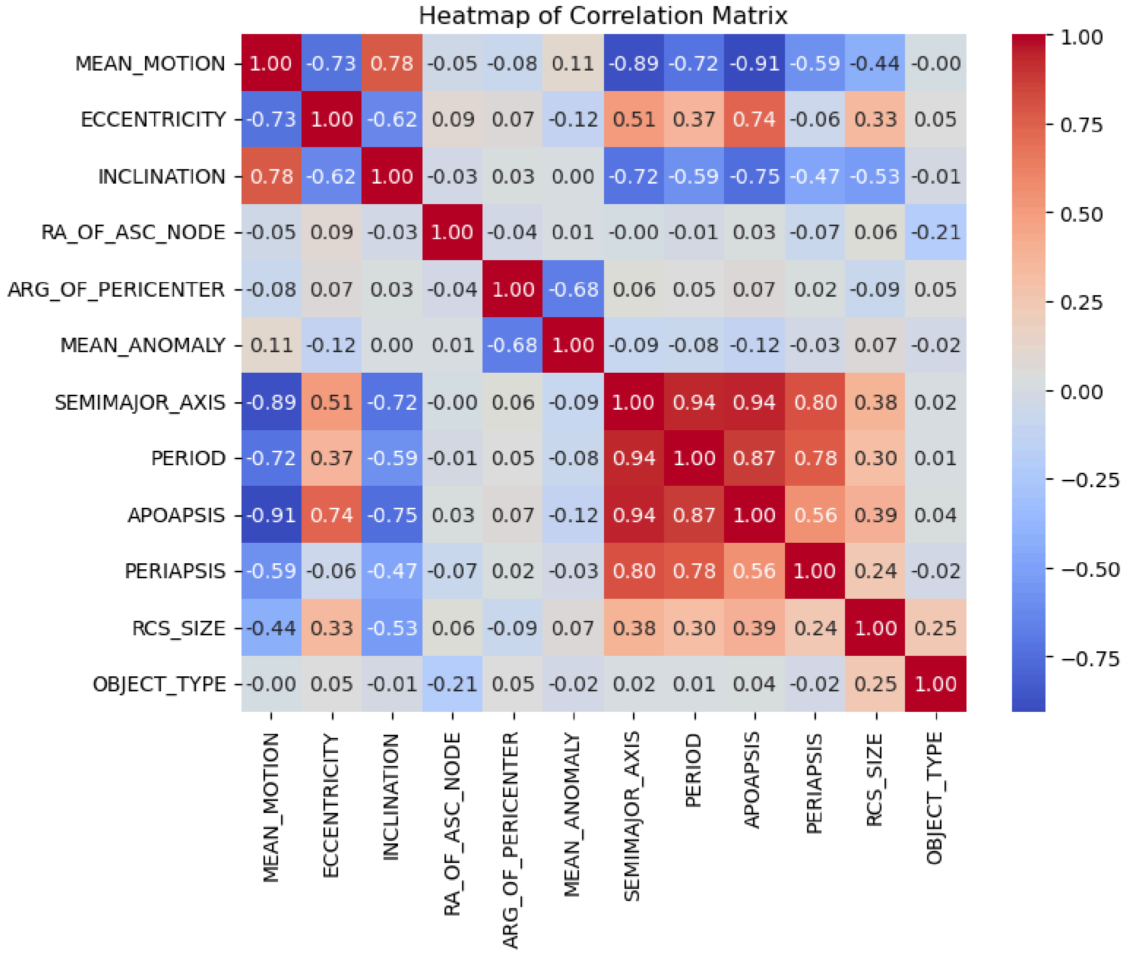


In [9]:
```python
balanced_data.describe()
```

Out[9]:

	MEAN_MOTION	ECCENTRICITY	INCLINATION	RA_OF_ASC_NODE	ARG_OF_PERICEN
count	33724.000000	33724.000000	33724.000000	33724.000000	33724.00
mean	11.694865	0.106806	69.736145	162.501443	170.16
std	5.284318	0.231139	32.331358	113.537065	100.69
min	0.051783	0.000005	0.001400	0.020000	0.00
25%	12.414438	0.001115	53.050475	52.609577	81.16
50%	14.418234	0.002457	82.584900	157.283356	164.35
75%	15.064096	0.017528	97.543300	266.604029	252.01
max	16.404097	0.897218	144.586200	359.967900	359.98

In [10]:
```python
# Calculate the correlation matrix
corr = balanced_data.corr()

# Create a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(corr, annot=True, fmt=".2f", cmap='coolwarm')
plt.title('Heatmap of Correlation Matrix')
plt.show()
```



In [11]:

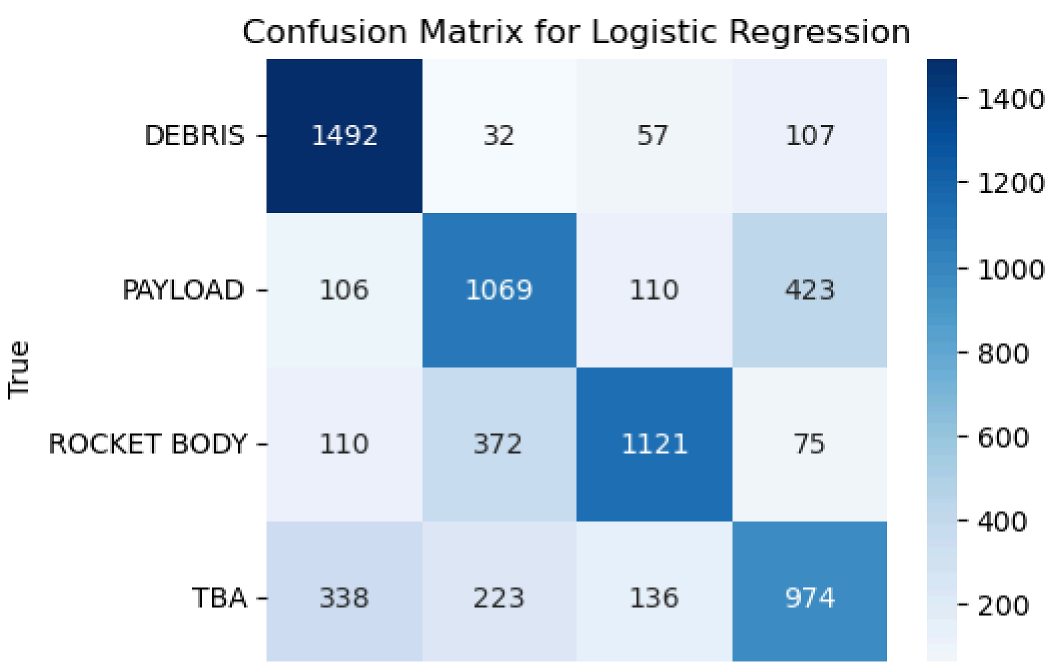
```
# Logistic Regression.

X = balanced_data.drop(['OBJECT_TYPE'], axis=1)  # Features
y = balanced_data['OBJECT_TYPE']  # Target variable

# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ra

# It's often a good practice to scale the features for models like Logistic
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize the Logistic Regression model
log_reg = LogisticRegression(max_iter=1000, random_state=42)

# Train the model
log_reg.fit(X_train_scaled, y_train)

# Make predictions
y_pred_log_reg = log_reg.predict(X_test_scaled)

# Evaluate the model
print("Logistic Regression Classification Report:")
print(classification_report(y_test, y_pred_log_reg))
print(f'The Accuracy Score of the Logistic Regression model is :- {accuracy
```

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

           0       0.73      0.88      0.80      1688
           1       0.63      0.63      0.63      1708
           2       0.79      0.67      0.72      1678
           3       0.62      0.58      0.60      1671

    accuracy                           0.69      6745
   macro avg       0.69      0.69      0.69      6745
weighted avg       0.69      0.69      0.69      6745

The Accuracy Score of the Logistic Regression model is :- 0.69028910303928
84
```

In [12]:
```python
# Calculate accuracy on the training set
train_accuracy_log_reg = accuracy_score(y_train, log_reg.predict(X_train_sc

# Calculate accuracy on the test set, using the previously computed 'y_pred_
test_accuracy_log_reg = accuracy_score(y_test, y_pred_log_reg)

print(f"Training Accuracy (Logistic Regression): {train_accuracy_log_reg}")
print(f"Test Accuracy (Logistic Regression): {test_accuracy_log_reg}")
print("It is as well fitting model because the model performs well on both
```

```
Training Accuracy (Logistic Regression): 0.7023610956670002
Test Accuracy (Logistic Regression): 0.6902891030392884
It is as well fitting model because the model performs well on both the tr
aining set and the test set, and the accuracies are
reasonably close, it suggests a good balance between bias and variance.
```

In [16]:
```python
# Confusion Matrix for Logistic Regression
cm2 = confusion_matrix(y_test, y_pred_log_reg)

# Plot confusion matrix
plt.figure(figsize=(5,4))
sns.heatmap(cm2, annot=True, fmt='g', cmap='Blues', xticklabels=encoder.cla
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix for Logistic Regression')
plt.show()
```



In [14]:
```
# Fine tuning of Logistic Regression Model.

parameters = {'C': [0.001, 0.01, 0.1, 1, 10, 100]}
log_reg_grid = GridSearchCV(LogisticRegression(max_iter=1000, random_state=
log_reg_grid.fit(X_train_scaled, y_train)

# Make predictions
y_pred_log_reg_grid = log_reg_grid.predict(X_test_scaled)

print(f'The Accuracy Score of the Logistic Regression model after fine tuni

# Calculate accuracy on the training set
train_accuracy_log_reg_grid = accuracy_score(y_train, log_reg_grid.predict(

# Calculate accuracy on the test set, using the previously computed 'y_pred_
test_accuracy_log_reg_grid = accuracy_score(y_test, y_pred_log_reg_grid)

print(f"Training Accuracy (Logistic Regression): {train_accuracy_log_reg_gr
print(f"Test Accuracy (Logistic Regression): {test_accuracy_log_reg_grid}")
```

```
The Accuracy Score of the Logistic Regression model after fine tuning is :
- 0.6934025203854707
Training Accuracy (Logistic Regression): 0.7061047481374403
Test Accuracy (Logistic Regression): 0.6934025203854707
```

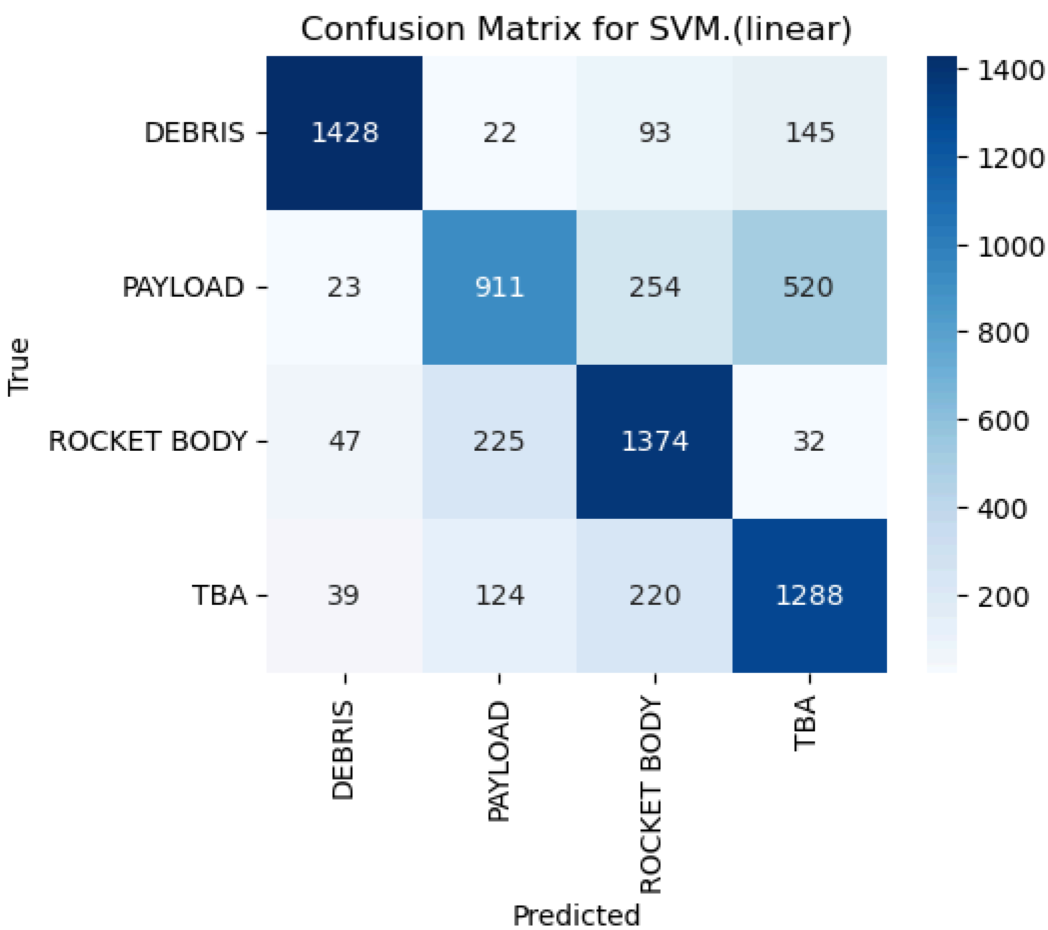
In [15]:
```
# SVM.(linear)

# Initialize the SVM model
svm_model = SVC(kernel='linear', random_state=42)  # 'linear' kernel is a c

# Train the model
svm_model.fit(X_train_scaled, y_train)

# Make predictions
y_pred_svm_linear = svm_model.predict(X_test_scaled)

# Evaluate the model
print("SVM Classification Report(Linear):")
print(classification_report(y_test, y_pred_svm_linear))
print(f'The Accuracy Score of the SVM Classification Report(Linear) model i
```

```
SVM Classification Report(Linear):
              precision    recall  f1-score   support

           0       0.93      0.85      0.89      1688
           1       0.71      0.53      0.61      1708
           2       0.71      0.82      0.76      1678
           3       0.65      0.77      0.70      1671

    accuracy                           0.74      6745
   macro avg       0.75      0.74      0.74      6745
weighted avg       0.75      0.74      0.74      6745

The Accuracy Score of the SVM Classification Report(Linear) model is :- 0.
7414381022979986
```

In [16]:
```
# Calculate accuracy on the training set
train_accuracy_svm_linear = accuracy_score(y_train, svm_model.predict(X_tra

# Use the previously computed 'y_pred_svm_linear' for test accuracy
test_accuracy_svm_linear = accuracy_score(y_test, y_pred_svm_linear)

print(f"Training Accuracy (SVM, Linear): {train_accuracy_svm_linear}")
print(f"Test Accuracy (SVM, Linear): {test_accuracy_svm_linear}")
print("This SVM (Linear) model neither significantly overfits nor severely
```

```
Training Accuracy (SVM, Linear): 0.7456169613403018
Test Accuracy (SVM, Linear): 0.7414381022979986
This SVM (Linear) model neither significantly overfits nor severely underf
its, but it does lean more towards underfitting due
to the not-so-high training accuracy.
```

In [17]:
```
# Confusion Matrix for SVM.(linear)
cm3 = confusion_matrix(y_test, y_pred_svm_linear)

# Plot confusion matrix
plt.figure(figsize=(5,4))
sns.heatmap(cm3, annot=True, fmt='g', cmap='Blues', xticklabels=encoder.cla
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix for SVM.(linear)')
plt.show()
```



In [18]:
```
# Fine Tuning of SVM(Linear) Model.

parameters_svm_linear = {'C': [0.1, 1, 10]}
svm_linear_grid = GridSearchCV(SVC(kernel='linear', random_state=42), param
svm_linear_grid.fit(X_train_scaled, y_train)

y_pred_svm_linear_grid = svm_linear_grid.predict(X_test_scaled)
print(f'The Accuracy Score of the SVM Classification Report(Linear) model a

# Calculate accuracy on the training set
train_accuracy_svm_linear_grid = accuracy_score(y_train, svm_linear_grid.pr

# Use the previously computed 'y_pred_svm_linear' for test accuracy
test_accuracy_svm_linear_grid = accuracy_score(y_test, y_pred_svm_linear_gr

print(f"Training Accuracy (SVM, Linear) after fine tuning : {train_accuracy
print(f"Test Accuracy (SVM, Linear)after fine tuning : {test_accuracy_svm_l
```

```
The Accuracy Score of the SVM Classification Report(Linear) model after fi
ne tuning is :- 0.7457375833951075
Training Accuracy (SVM, Linear) after fine tuning : 0.7479521109010712
Test Accuracy (SVM, Linear)after fine tuning : 0.7457375833951075
```

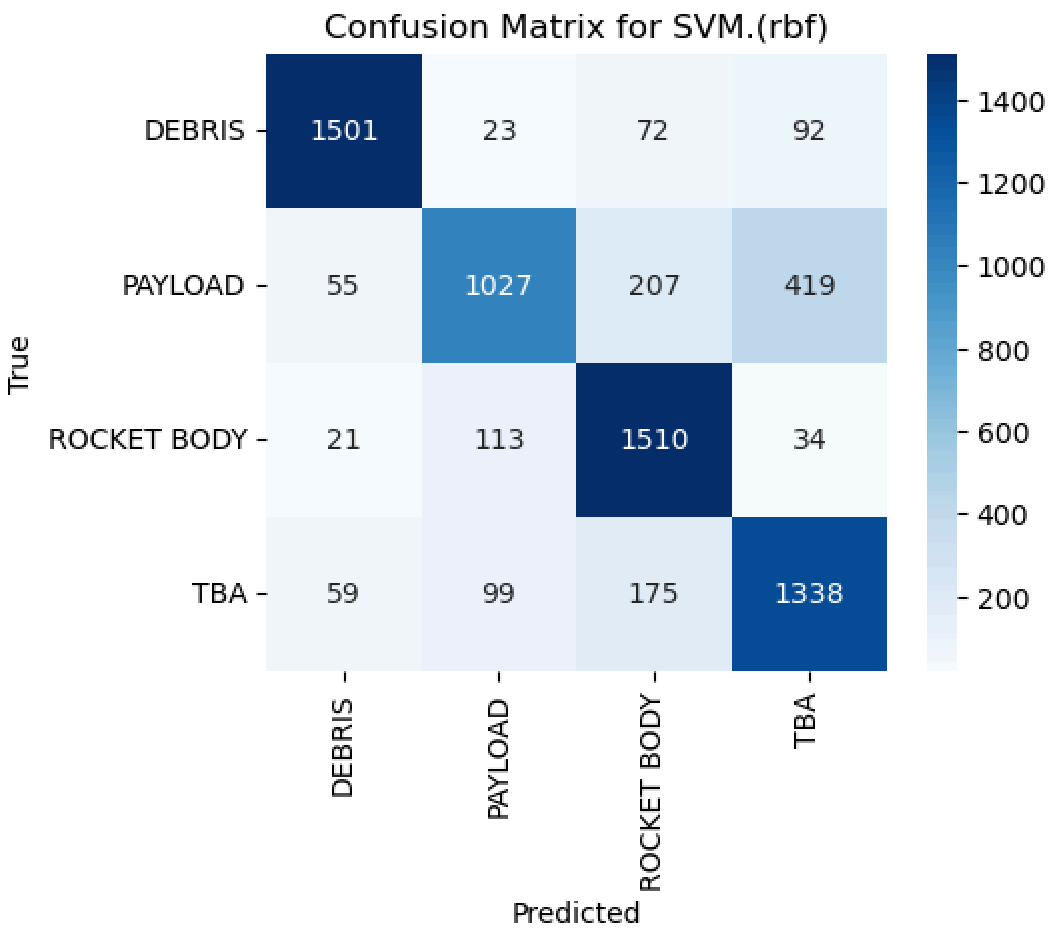
In [19]:
```
# SVM.(rbf = Radial Basis function)

# Initialize the SVM model
svm_model = SVC(kernel='rbf', random_state=42)  # 'linear' kernel is a comm

# Train the model
svm_model.fit(X_train_scaled, y_train)

# Make predictions
y_pred_svm_rbf = svm_model.predict(X_test_scaled)

# Evaluate the model
print("SVM Classification Report:")
print(classification_report(y_test, y_pred_svm_rbf))
print(f'The Accuracy Score of the SVM Classification Report(rbf) model is :
```

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

           0       0.92      0.89      0.90      1688
           1       0.81      0.60      0.69      1708
           2       0.77      0.90      0.83      1678
           3       0.71      0.80      0.75      1671

    accuracy                           0.80      6745
   macro avg       0.80      0.80      0.79      6745
weighted avg       0.80      0.80      0.79      6745

The Accuracy Score of the SVM Classification Report(rbf) model is :- 0.797
0348406226835
```

In [20]:
```
# Calculate accuracy on the training set
train_accuracy_svm_rbf = accuracy_score(y_train, svm_model.predict(X_train_

# You've already computed 'y_pred_svm_rbf' for the test set
test_accuracy_svm_rbf = accuracy_score(y_test, y_pred_svm_rbf)

print(f"Training Accuracy (SVM, RBF): {train_accuracy_svm_rbf}")
print(f"Test Accuracy (SVM, RBF): {test_accuracy_svm_rbf}")
print("This Model indicates a well-fitted model with a good balance between
```

```
Training Accuracy (SVM, RBF): 0.8062567181882204
Test Accuracy (SVM, RBF): 0.7970348406226835
This Model indicates a well-fitted model with a good balance between bias
and variance.
```

In [21]:
```
# Confusion Matrix for SVM.(rbf)
cm4 = confusion_matrix(y_test, y_pred_svm_rbf)

# Plot confusion matrix
plt.figure(figsize=(5, 4))
sns.heatmap(cm4, annot=True, fmt='g', cmap='Blues', xticklabels=encoder.cla
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix for SVM.(rbf)')
plt.show()
```



In [22]:
```
# Fine Tuning of SVM(rbf) Model.

parameters_svm = {'C': [0.1, 1, 10], 'gamma': [0.001, 0.01, 0.1, 1]}
svm_rbf_grid = GridSearchCV(SVC(kernel='rbf', random_state=42), parameters_
svm_rbf_grid.fit(X_train_scaled, y_train)

y_pred_svm_rbf_grid = svm_rbf_grid.predict(X_test_scaled)
print(f'The Accuracy Score of the SVM Classification Report(rbf) model afte

# Calculate accuracy on the training set
train_accuracy_svm_rbf_grid = accuracy_score(y_train, svm_rbf_grid.predict(

# Use the previously computed 'y_pred_svm_linear' for test accuracy
test_accuracy_svm_rbf_grid = accuracy_score(y_test, y_pred_svm_rbf_grid)

print(f"Training Accuracy (SVM, rbf) after fine tuning : {train_accuracy_sv
print(f"Test Accuracy (SVM, rbf)after fine tuning : {test_accuracy_svm_rbf_
```

```
The Accuracy Score of the SVM Classification Report(rbf) model after fine
tuning is :- 0.9272053372868791
Training Accuracy (SVM, rbf) after fine tuning : 0.9455502427814226
Test Accuracy (SVM, rbf)after fine tuning : 0.9272053372868791
```

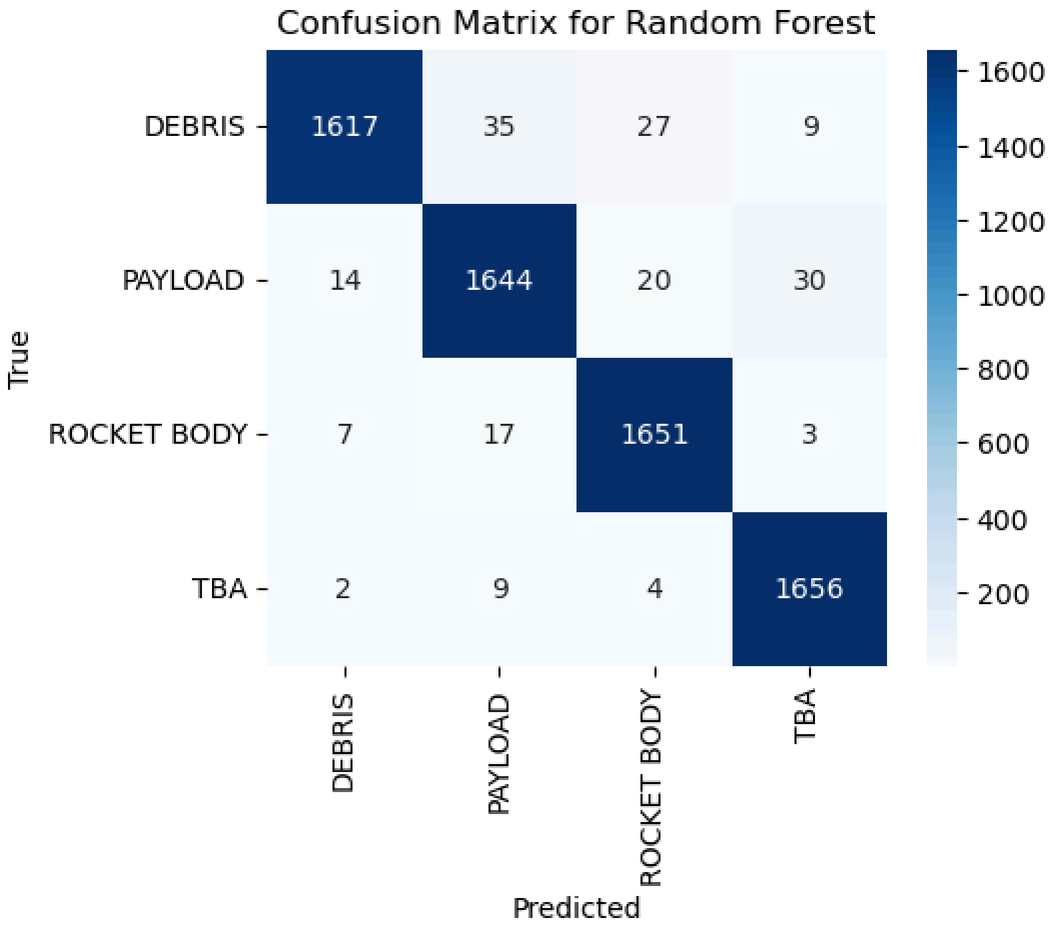
In [23]:
```
# Random Forest.

# Split the dataset into features and target variable
X = balanced_data.drop('OBJECT_TYPE', axis=1)  # Features
y = balanced_data['OBJECT_TYPE']  # Target variable

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ra

# Initialize and train the Random Forest Classifier
clf = RandomForestClassifier(n_estimators=100, random_state=42)
clf.fit(X_train, y_train)

# Predictions
y_pred = clf.predict(X_test)

# Evaluate the model
print("Random Forest Classification Report:")
print(classification_report(y_test, y_pred))
print(f'The Accuracy Score of the Random Forest model is :- {accuracy_score
```

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

           0       0.99      0.96      0.97      1688
           1       0.96      0.96      0.96      1708
           2       0.97      0.98      0.98      1678
           3       0.98      0.99      0.98      1671

    accuracy                           0.97      6745
   macro avg       0.97      0.97      0.97      6745
weighted avg       0.97      0.97      0.97      6745

The Accuracy Score of the Random Forest model is :- 0.9737583395107487
```

In [24]:
```
# Calculate accuracy on the training set
train_accuracy = accuracy_score(y_train, clf.predict(X_train))

# Calculate accuracy on the test set
test_accuracy = accuracy_score(y_test, y_pred)

print(f"Training Accuracy: {train_accuracy}")
print(f"Test Accuracy: {test_accuracy}")
print("The Training and Testing Accuracy values are both higher indicates a
```

```
Training Accuracy: 1.0
Test Accuracy: 0.9737583395107487
The Training and Testing Accuracy values are both higher indicates a well-
fitting model with low bias and low variance
```

In [25]:
```
# Confusion Matrix for Random Forest.
cm = confusion_matrix(y_test, y_pred)

# Plot confusion matrix
plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, fmt='g', cmap='Blues', xticklabels=encoder.clas
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix for Random Forest')
plt.show()
```



In [28]:
```
# Fine Tuning of Random Forest

parameters_rf = {
    'n_estimators': [50, 100, 150],
    'max_depth': [0, 10, 20],
    'min_samples_split': [2, 5, 8],
    'min_samples_leaf': [1, 2, 4]
}
rf_grid = GridSearchCV(RandomForestClassifier(random_state=42), parameters_
rf_grid.fit(X_train, y_train)  # Note: Random Forest doesn't require scaled

# Predictions
y_pred = rf_grid.predict(X_test)

print(f'The Accuracy Score of the Random Forest model after tuning is :- {a

# Calculate accuracy on the training set
train_accuracy_rf = accuracy_score(y_train, rf_grid.predict(X_train))

# Calculate accuracy on the test set
test_accuracy_rf = accuracy_score(y_test, y_pred)

print(f"Training Accuracy after tuning:- {train_accuracy_rf}")
print(f"Test Accuracy after tuning:- {test_accuracy_rf}")
```

```
C:\ProgramData\anaconda3\lib\site-packages\sklearn\model_selection\_valida
tion.py:378: FitFailedWarning:
135 fits failed out of a total of 405.
The score on these train-test partitions for these parameters will be set
to nan.
If these failures are not expected, you can try to debug them by setting e
rror_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------
------
135 fits failed with the following error:
Traceback (most recent call last):
  File "C:\ProgramData\anaconda3\lib\site-packages\sklearn\model_selection
\_validation.py", line 686, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "C:\ProgramData\anaconda3\lib\site-packages\sklearn\ensemble\_fores
t.py", line 340, in fit
    self._validate_params()
  File "C:\ProgramData\anaconda3\lib\site-packages\sklearn\base.py", line
581, in _validate_params
    validate_parameter_constraints(
  File "C:\ProgramData\anaconda3\lib\site-packages\sklearn\utils\_param_va
lidation.py", line 97, in validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_depth' par
ameter of RandomForestClassifier must be an int in the range [1, inf) or N
one. Got 0 instead.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
C:\ProgramData\anaconda3\lib\site-packages\sklearn\model_selection\_searc
h.py:952: UserWarning: One or more of the test scores are non-finite: [
nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan        nan        nan        nan
        nan        nan        nan 0.93824841 0.93817428 0.93750712
 0.93747    0.93554251 0.93550547 0.93428237 0.93583911 0.93602445
 0.93598736 0.93706224 0.93639504 0.9362838  0.93572781 0.93572782
 0.93546847 0.9360986  0.93509775 0.93294794 0.93424521 0.93380045
 0.93294794 0.93424521 0.93380045 0.93294794 0.93424521 0.93380045
 0.9686423  0.96997664 0.97023614 0.96797519 0.96893888 0.9686053
 0.96630717 0.96678904 0.96652959 0.96627009 0.96660365 0.96715964
 0.96675186 0.9667519  0.96738202 0.96397201 0.96460217 0.96478744
 0.96100675 0.96148859 0.96174806 0.96100675 0.96148859 0.96174806
 0.96100675 0.96148859 0.96174806]
  warnings.warn(

The Accuracy Score of the Random Forest model after tuning is :- 0.9739065
974796145
Training Accuracy after tuning:- 0.9988880240186812
Test Accuracy after tuning:- 0.9739065974796145
```

In [29]:
```
accuracies = {
    "Model": ["Logistic Regression", "SVM (Linear)", "SVM (RBF)", "Random F
    "Training Accuracy": [
        train_accuracy_log_reg,
        train_accuracy_svm_linear,
        train_accuracy_svm_rbf,
        train_accuracy
    ],
    "Testing Accuracy": [
        accuracy_score(y_test, y_pred_log_reg),  # Logistic Regression test
        accuracy_score(y_test, y_pred_svm_linear),  # SVM (Linear) test acc
        accuracy_score(y_test, y_pred_svm_rbf),  # SVM (RBF) test accuracy
        accuracy_score(y_test, y_pred)  # Random Forest test accuracy
    ],
    "Tuned Training Accuracy": [
        train_accuracy_log_reg_grid,
        train_accuracy_svm_linear_grid,
        train_accuracy_svm_rbf_grid,
        train_accuracy_rf
    ],
    "Tuned Testing Accuracy": [
        test_accuracy_log_reg_grid,
        test_accuracy_svm_linear_grid,
        test_accuracy_svm_rbf_grid,
        test_accuracy_rf
    ]
}

# Create a DataFrame
accuracy_df = pd.DataFrame(accuracies)

# Display the DataFrame
accuracy_df
```

Out[29]:

	Model	Training Accuracy	Testing Accuracy	Tuned Training Accuracy	Tuned Testing Accuracy
0	Logistic Regression	0.702361	0.690289	0.706105	0.693403
1	SVM (Linear)	0.745617	0.741438	0.747952	0.745738
2	SVM (RBF)	0.806257	0.797035	0.945550	0.927205
3	Random Forest	1.000000	0.973907	0.998888	0.973907