In [23]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import zscore
from sklearn.preprocessing import MinMaxScaler, OneHotEncoder
from sklearn.decomposition import PCA
import numpy as np
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectFromModel
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectFromModel
from scipy import stats
from sklearn.decomposition import PCA
from scipy.stats import chi2_contingency
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import classification_report, accuracy_score
from sklearn.preprocessing import PolynomialFeatures
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoosti
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import cross_val_score
from xgboost import XGBClassifier
from sklearn.model_selection import KFold, cross_val_score
from sklearn.metrics import classification_report, roc_auc_score
import warnings
import joblib
```

In [24]:
```
# Suppress warnings
warnings.filterwarnings("ignore")
```

In [25]:
```
# Load the cleaned dataset
df = pd.read_csv("Network_anomaly_data.csv")

# Check the first few rows of the data
print(df.head())

# Get general information about the dataset
print(df.info())
```

```
   duration protocoltype   service flag  srcbytes  dstbytes  land  \
0         0          tcp  ftp_data   SF       491         0     0
1         0          udp     other   SF       146         0     0
2         0          tcp   private   S0         0         0     0
3         0          tcp      http   SF       232      8153     0
4         0          tcp      http   SF       199       420     0
```

```
   wrongfragment  urgent  hot  ...  dsthostsamesrvrate  dsthostdif
fsrvrate  \
0              0       0    0  ...                0.17
0.03
1              0       0    0  ...                0.00
0.60
2              0       0    0  ...                0.10
0.05
3              0       0    0  ...                1.00
0.00
4              0       0    0  ...                1.00
0.00

   dsthostsamesrcportrate  dsthostsrvdiffhostrate  dsthostserrorra
te  \
0                    0.17                    0.00               0.
00
1                    0.88                    0.00               0.
00
2                    0.00                    0.00               1.
00
3                    0.03                    0.04               0.
03
4                    0.00                    0.00               0.
00

   dsthostsrvserrorrate  dsthostrerrorrate  dsthostsrvrerrorrate
attack  \
0                  0.00               0.05                  0.00
normal
1                  0.00               0.00                  0.00
normal
2                  1.00               0.00                  0.00
neptune
3                  0.01               0.00                  0.01
normal
4                  0.00               0.00                  0.00
normal

   lastflag
0        20
1        15
2        19
3        21
4        21

[5 rows x 43 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 125973 entries, 0 to 125972
Data columns (total 43 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   duration                125973 non-null  int64
```

```
 1   protocoltype            125973 non-null  object
 2   service                 125973 non-null  object
 3   flag                    125973 non-null  object
 4   srcbytes                125973 non-null  int64
 5   dstbytes                125973 non-null  int64
 6   land                    125973 non-null  int64
 7   wrongfragment           125973 non-null  int64
 8   urgent                  125973 non-null  int64

 9   hot                     125973 non-null  int64
 10  numfailedlogins         125973 non-null  int64
 11  loggedin                125973 non-null  int64
 12  numcompromised          125973 non-null  int64
 13  rootshell               125973 non-null  int64
 14  suattempted             125973 non-null  int64
 15  numroot                 125973 non-null  int64
 16  numfilecreations        125973 non-null  int64
 17  numshells               125973 non-null  int64
 18  numaccessfiles          125973 non-null  int64
 19  numoutboundcmds         125973 non-null  int64
 20  ishostlogin             125973 non-null  int64
 21  isguestlogin            125973 non-null  int64
 22  count                   125973 non-null  int64
 23  srvcount                125973 non-null  int64
 24  serrorrate              125973 non-null  float64
 25  srvserrorrate           125973 non-null  float64
 26  rerrorrate              125973 non-null  float64
 27  srvrerrorrate           125973 non-null  float64
 28  samesrvrate             125973 non-null  float64
 29  diffsrvrate             125973 non-null  float64
 30  srvdiffhostrate         125973 non-null  float64
 31  dsthostcount            125973 non-null  int64
 32  dsthostsrvcount         125973 non-null  int64
 33  dsthostsamesrvrate      125973 non-null  float64
 34  dsthostdiffsrvrate      125973 non-null  float64
 35  dsthostsamesrcportrate  125973 non-null  float64
 36  dsthostsrvdiffhostrate  125973 non-null  float64
 37  dsthostserrorrate       125973 non-null  float64
 38  dsthostsrvserrorrate    125973 non-null  float64
 39  dsthostrerrorrate       125973 non-null  float64
 40  dsthostsrvrerrorrate    125973 non-null  float64
 41  attack                  125973 non-null  object
 42  lastflag                125973 non-null  int64
dtypes: float64(15), int64(24), object(4)
memory usage: 41.3+ MB
None
```

In [26]:
```
# Display missing values before handling
print("Missing values before handling:")
print(df.isnull().sum())
```

```
Missing values before handling:
duration                  0
protocoltype              0
service                   0
flag                      0
srcbytes                  0
dstbytes                  0
land                      0
wrongfragment             0
urgent                    0
hot                       0
numfailedlogins           0
loggedin                  0
numcompromised            0
rootshell                 0
suattempted               0
numroot                   0
numfilecreations          0
numshells                 0
numaccessfiles            0
numoutboundcmds           0
ishostlogin               0
isguestlogin              0
count                     0
srvcount                  0
serrorrate                0
srvserrorrate             0
rerrorrate                0
srvrerrorrate             0
samesrvrate               0
diffsrvrate               0
srvdiffhostrate           0
dsthostcount              0
dsthostsrvcount           0
dsthostsamesrvrate        0
dsthostdiffsrvrate        0
dsthostsamesrcportrate    0
dsthostsrvdiffhostrate    0
dsthostserrorrate         0
dsthostsrvserrorrate      0
dsthostrerrorrate         0
dsthostsrvrerrorrate      0
attack                    0
lastflag                  0
dtype: int64
```

In [27]:
```
# Separate numerical and categorical columns
numerical_columns = df.select_dtypes(include=['float64', 'int64']).
categorical_columns = df.select_dtypes(include=['object']).columns

# Replace missing values in numerical columns with the median
for col in numerical_columns:
    df[col].fillna(df[col].median(), inplace=True)

# Replace missing values in categorical columns with the most frequ
for col in categorical_columns:
    df[col].fillna(df[col].mode()[0], inplace=True)
```

In [28]:
```
# Display missing values after handling
print("\nMissing values after handling:")
print(df.isnull().sum())
```

```
Missing values after handling:
duration                    0
protocoltype                0
service                     0
flag                        0
srcbytes                    0
dstbytes                    0
land                        0
wrongfragment               0
urgent                      0
hot                         0
numfailedlogins             0
loggedin                    0
numcompromised              0
rootshell                   0
suattempted                 0
numroot                     0
numfilecreations            0
numshells                   0
numaccessfiles              0
numoutboundcmds             0
ishostlogin                 0
isguestlogin                0
count                       0
srvcount                    0
serrorrate                  0
srvserrorrate               0
rerrorrate                  0
srvrerrorrate               0
samesrvrate                 0
diffsrvrate                 0
srvdiffhostrate             0
dsthostcount                0
dsthostsrvcount             0
dsthostsamesrvrate          0
dsthostdiffsrvrate          0
dsthostsamesrcportrate      0
dsthostsrvdiffhostrate      0
dsthostserrorrate           0
dsthostsrvserrorrate        0
dsthostrerrorrate           0
dsthostsrvrerrorrate        0
attack                      0
lastflag                    0
dtype: int64
```

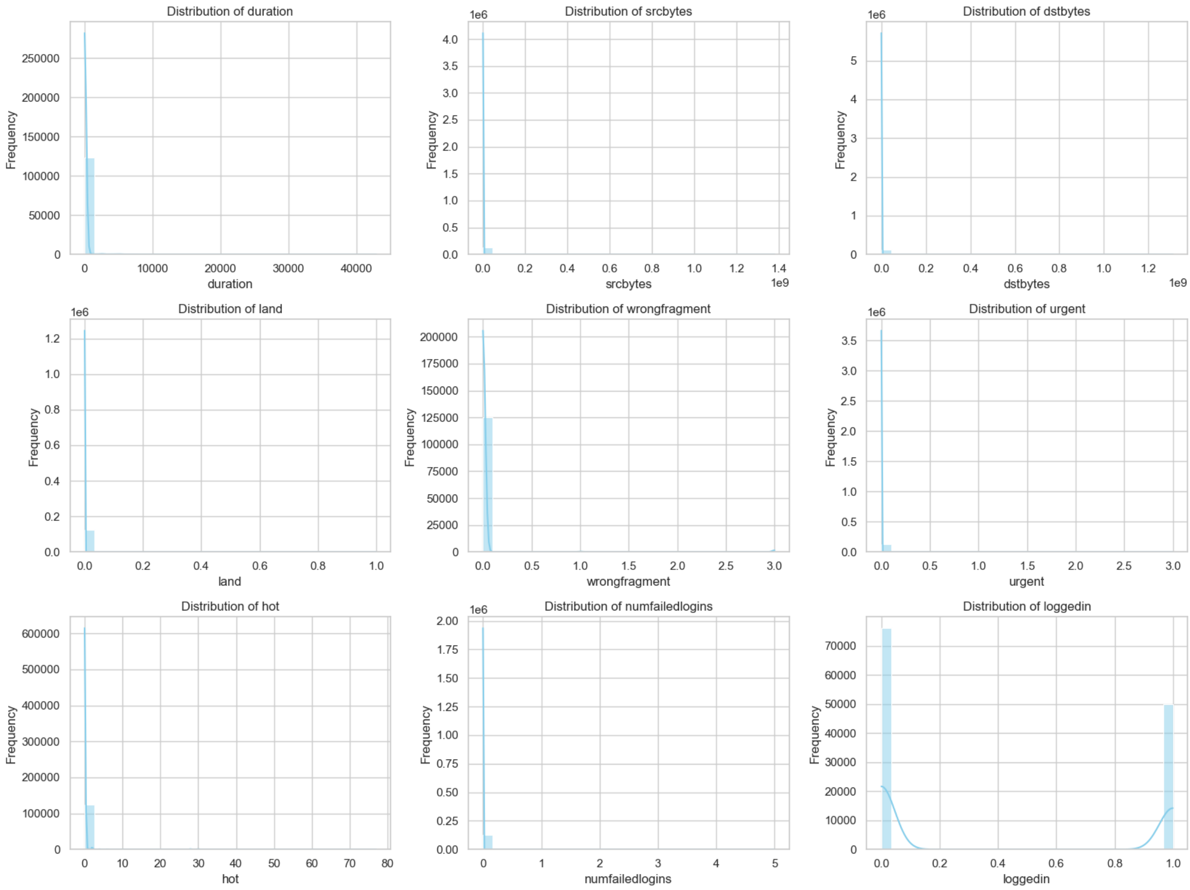
In [29]:
```
# Set plot style
sns.set(style="whitegrid")

# Function to plot the distribution of numeric features
def plot_feature_distributions(data, feature_columns):
    n_cols = 3
    n_rows = (len(feature_columns) + n_cols - 1) // n_cols
    plt.figure(figsize=(16, n_rows * 4))

    for i, feature in enumerate(feature_columns, 1):
        plt.subplot(n_rows, n_cols, i)
        sns.histplot(data[feature], kde=True, bins=30, color="skybl
        plt.title(f"Distribution of {feature}")
        plt.xlabel(feature)
        plt.ylabel("Frequency")

    plt.tight_layout()
    plt.show()

# Select numeric columns for distribution analysis
numeric_columns = df.select_dtypes(include=['int64', 'float64']).co
plot_feature_distributions(df, numeric_columns[:9])  # Plot for the
```



Observations:

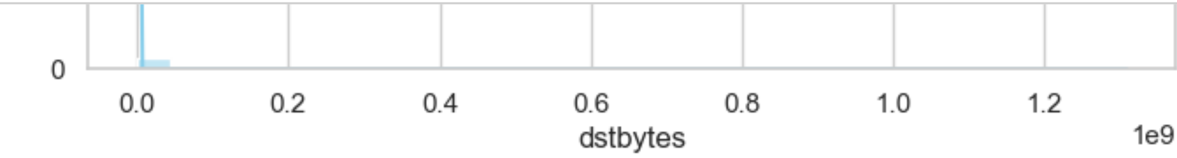
Features like duration, srcbytes, and dstbytes have highly skewed distributions, likely influenced by extreme outliers or infrequent high values. Binary features such as land and urgent show a discrete distribution. Some features, like wrongfragment, have a significant number of zero entries, indicating sparsity.

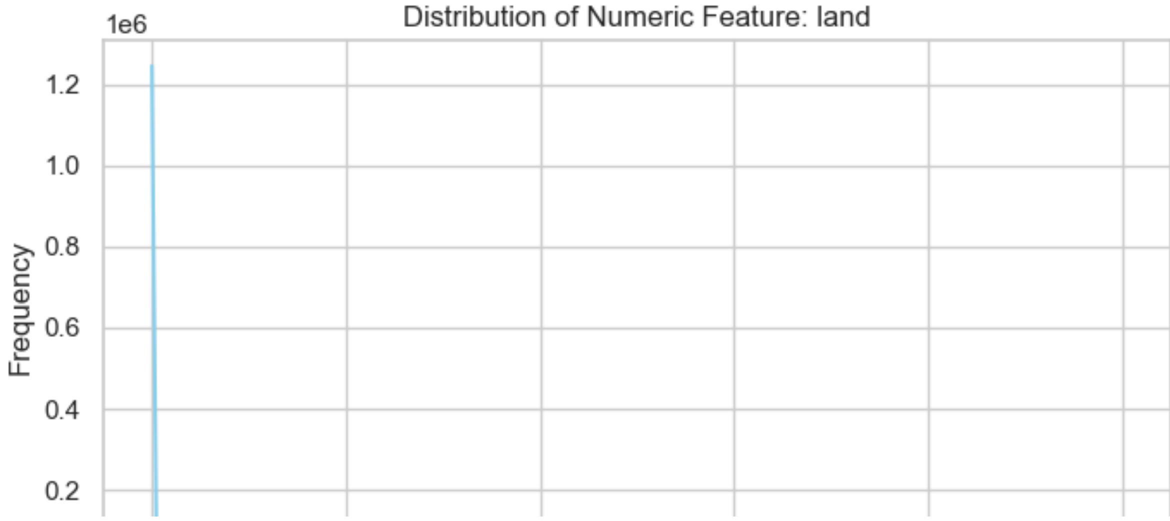
In [30]:
```
def plot_distributions(data):
    # Separate numeric and categorical columns
    numeric_columns = data.select_dtypes(include=['int64', 'float64
    categorical_columns = data.select_dtypes(include=['object', 'ca

    # Plot distributions for numeric features
    for column in numeric_columns:
        plt.figure(figsize=(8, 4))
        sns.histplot(data[column], kde=True, bins=30, color="skyblu
        plt.title(f"Distribution of Numeric Feature: {column}")
        plt.xlabel(column)
        plt.ylabel("Frequency")
        plt.show()

    # Plot distributions for categorical features
    for column in categorical_columns:
        plt.figure(figsize=(8, 4))
        sns.countplot(data=data, x=column, palette="viridis")
        plt.title(f"Distribution of Categorical Feature: {column}")
        plt.xlabel(column)
        plt.ylabel("Count")
        plt.xticks(rotation=45)
        plt.show()
```

In [31]:
```
# Call the function to visualize all feature distributions
plot_distributions(df)
```





Corelation

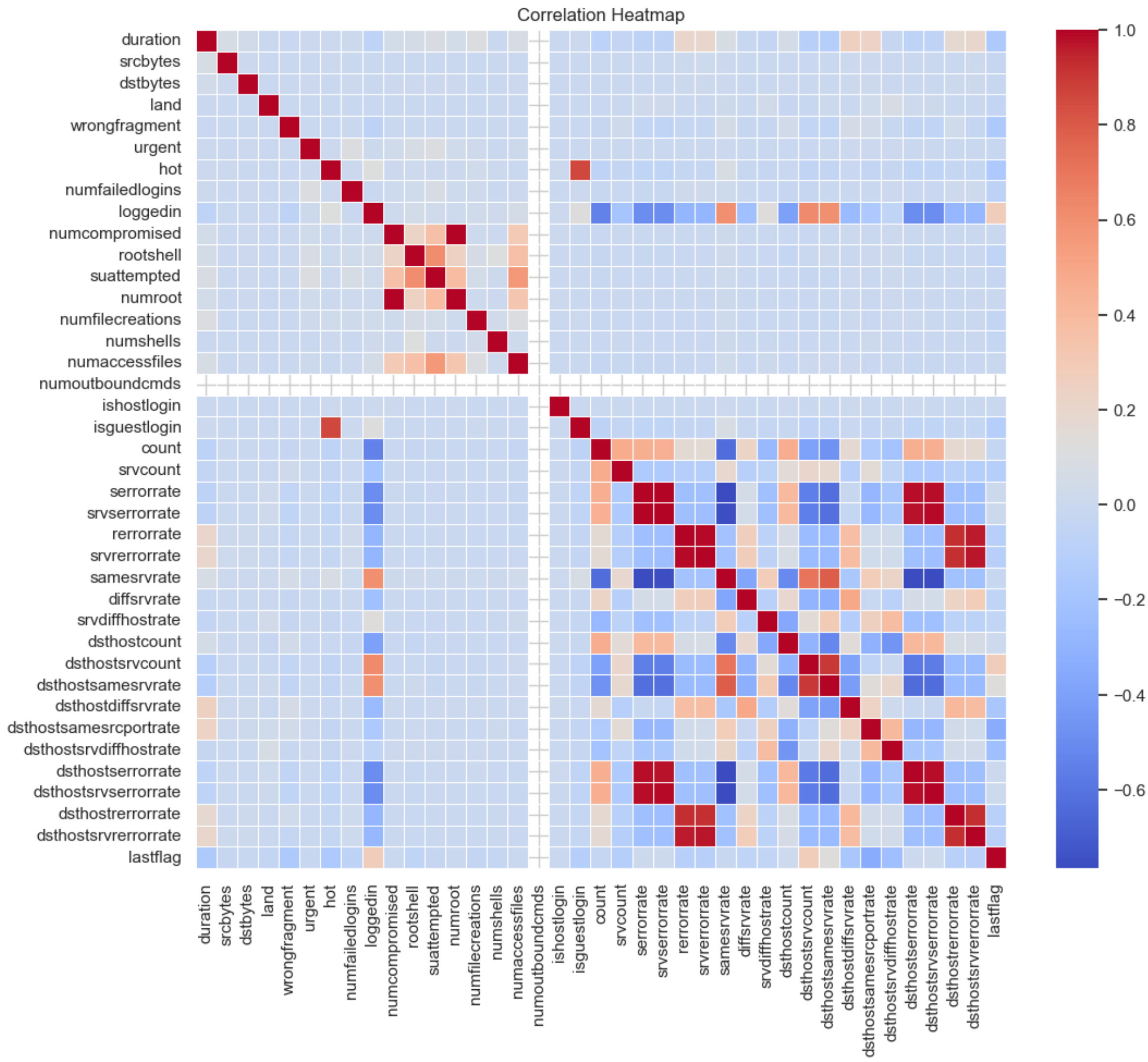
To identify highly correlated features in your dataset and drop the ones that are redundant, we can calculate the correlation matrix and use a threshold to decide which features to drop.

In [32]:
```
def correlation_analysis(data):
    # Compute the correlation matrix
    # Identify numerical columns to scale/normalize
    numerical_columns = data.select_dtypes(include=['float64', 'int
    corr_matrix = data[numerical_columns].corr()

    # Plot the heatmap
    plt.figure(figsize=(12, 10))
    sns.heatmap(corr_matrix, annot=False, cmap="coolwarm", fmt='.2f
    plt.title("Correlation Heatmap")
    plt.show()

    # Return the correlation matrix for further analysis
    return corr_matrix
```

In [33]:
```
# Call the function for correlation analysis
correlation_matrix = correlation_analysis(df)
```



In [34]:
```
# Check for duplicates
print(f"Number of duplicates before removal: {df.duplicated().sum()

# Remove duplicates
df_cleaned = df.drop_duplicates()

# Verify if duplicates are removed
print(f"Number of duplicates after removal: {df_cleaned.duplicated(
```

```
Number of duplicates before removal: 0
Number of duplicates after removal: 0
```

In [35]:
```
categorical_columns = ['protocoltype', 'service', 'flag']

# Dictionary to store mappings
label_encoders = {}
label_mappings = {}

# Apply Label Encoding and store mappings
for col in categorical_columns:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le
    label_mappings[col] = {index: label for index, label in enumera

# Print the mappings for each column
for col, mapping in label_mappings.items():
    print(f"Mapping for {col}:")
    for encoded, original in mapping.items():
        print(f"  {encoded} -> {original}")
    print()

# Display the first few rows of the dataset
print("\nEncoded Dataset:")
print(df.head())
```

```
  27 -> http_8001
  28 -> imap4
  29 -> iso_tsap
  30 -> klogin
  31 -> kshell
  32 -> ldap
  33 -> link
  34 -> login
  35 -> mtp
  36 -> name
  37 -> netbios_dgm
  38 -> netbios_ns
  39 -> netbios_ssn
  40 -> netstat
  41 -> nnsp
  42 -> nntp
  43 -> ntp_u
  44 -> other
  45 -> pm_dump
  46 -> pop_2
```

In [36]:
```
# Identify numerical columns to scale/normalize
numerical_columns = df.select_dtypes(include=['float64', 'int64']).

# Standardization: Mean = 0, Std Dev = 1
standard_scaler = StandardScaler()
df_standardized = df.copy()
df_standardized[numerical_columns] = standard_scaler.fit_transform(
```

```
# Normalization: Scale to range [0, 1]
minmax_scaler = MinMaxScaler()
df_normalized = df.copy()
df_normalized[numerical_columns] = minmax_scaler.fit_transform(df[n

# Display the transformed datasets
print("Standardized Dataset (first 5 rows):")
print(df_standardized.head())

print("\nNormalized Dataset (first 5 rows):")
print(df_normalized.head())
```

```
Standardized Dataset (first 5 rows):
   duration  protocoltype   service      flag  srcbytes  dstbytes
land  \
0 -0.110249     -0.124706 -0.686785  0.751111 -0.007679 -0.004919
-0.014089
1 -0.110249      2.219312  0.781428  0.751111 -0.007737 -0.004919
-0.014089
2 -0.110249     -0.124706  1.087305 -0.736235 -0.007762 -0.004919
-0.014089
3 -0.110249     -0.124706 -0.442083  0.751111 -0.007723 -0.002891
-0.014089
4 -0.110249     -0.124706 -0.442083  0.751111 -0.007728 -0.004814
-0.014089

   wrongfragment    urgent       hot  ...  dsthostsamesrvrate  \
0      -0.089486 -0.007736 -0.095076  ...           -0.782367
1      -0.089486 -0.007736 -0.095076  ...           -1.161030
2      -0.089486 -0.007736 -0.095076  ...           -0.938287
3      -0.089486 -0.007736 -0.095076  ...            1.066401
4      -0.089486 -0.007736 -0.095076  ...            1.066401

   dsthostdiffsrvrate  dsthostsamesrcportrate  dsthostsrvdiffhostr
ate  \
0           -0.280282                0.069972               -0.289
103
1            2.736852                2.367737               -0.289
103
2           -0.174417               -0.480197               -0.289
103
3           -0.439078               -0.383108                0.066
252
4           -0.439078               -0.480197               -0.289
103

   dsthostserrorrate  dsthostsrvserrorrate  dsthostrerrorrate  \
0          -0.639532             -0.624871          -0.224532
1          -0.639532             -0.624871          -0.387635
2           1.608759              1.618955          -0.387635
3          -0.572083             -0.602433          -0.387635
4          -0.639532             -0.624871          -0.387635

   dsthostsrvrerrorrate   attack  lastflag
```

```
0           -0.376387   normal  0.216426
1           -0.376387   normal -1.965556
2           -0.376387  neptune -0.219970
3           -0.345084   normal  0.652823
4           -0.376387   normal  0.652823

[5 rows x 43 columns]

Normalized Dataset (first 5 rows):
   duration  protocoltype   service  flag      srcbytes      dstby
tes  land  \
0       0.0           0.5  0.289855   0.9  3.558064e-07  0.000000e
+00   0.0
1       0.0           1.0  0.637681   0.9  1.057999e-07  0.000000e
+00   0.0
2       0.0           0.5  0.710145   0.5  0.000000e+00  0.000000e
+00   0.0
3       0.0           0.5  0.347826   0.9  1.681203e-07  6.223962e
-06   0.0
4       0.0           0.5  0.347826   0.9  1.442067e-07  3.206260e

-07   0.0

   wrongfragment  urgent  hot  ...  dsthostsamesrvrate  dsthostdif
fsrvrate  \
0            0.0     0.0  0.0  ...                0.17
0.03
1            0.0     0.0  0.0  ...                0.00
0.60
2            0.0     0.0  0.0  ...                0.10
0.05
3            0.0     0.0  0.0  ...                1.00
0.00
4            0.0     0.0  0.0  ...                1.00
0.00

   dsthostsamesrcportrate  dsthostsrvdiffhostrate  dsthostserrorra
te  \
0                    0.17                    0.00                0.
00
1                    0.88                    0.00                0.
00
2                    0.00                    0.00                1.
00
3                    0.03                    0.04                0.
03
4                    0.00                    0.00                0.
00

   dsthostsrvserrorrate  dsthostrerrorrate  dsthostsrvrerrorrate
attack  \
0                  0.00               0.05                  0.00
normal
1                  0.00               0.00                  0.00
```

```
normal
2                   1.00              0.00                   0.00
neptune
3                   0.01              0.00                   0.01
normal
4                   0.00              0.00                   0.00
normal

   lastflag
0  0.952381
1  0.714286
2  0.904762
3  1.000000
4  1.000000

[5 rows x 43 columns]
```

Explanation of Changes:

Dropping Only One Feature from Each Pair:

For each correlated pair, only the first feature (i.e., pair[0]) is added to the correlated_features set, ensuring that only one feature from each correlated pair is dropped.

Set Data Structure for Features to Drop:

A set is used to ensure that each feature is only added once, even if it appears in multiple correlated pairs.

In [37]:
```
# Select only numeric fields
numeric_df = df.select_dtypes(include=[np.number])

# Calculate the correlation matrix
correlation_matrix = numeric_df.corr()

# Set a threshold for correlation (e.g., 0.9)
threshold = 0.9

# Initialize a list to store correlated column pairs
correlated_pairs = []

# Find highly correlated features
for i in range(len(correlation_matrix.columns)):
    for j in range(i):
        if abs(correlation_matrix.iloc[i, j]) > threshold:  # Check
            colname1 = correlation_matrix.columns[i]
            colname2 = correlation_matrix.columns[j]
            correlated_pairs.append((colname1, colname2))

# Print correlated column pairs
```

```
if correlated_pairs:
    print("Highly correlated column pairs (correlation > 0.9):")
    for pair in correlated_pairs:
        print(f"{pair[0]} and {pair[1]}")
else:
    print("No highly correlated column pairs found.")

# Initialize a set to keep track of features to drop
correlated_features = set()

# Keep only the first feature of each correlated pair (drop the sec
for pair in correlated_pairs:
    correlated_features.add(pair[0])  # Add only the first feature

# Drop the selected features from the original dataframe
df = df.drop(columns=correlated_features)

# Output the dropped features
print(f"\nDropped features due to high correlation: {correlated_fea
```

```
Highly correlated column pairs (correlation > 0.9):
numroot and numcompromised
srvserrorrate and serrorrate
srvrerrorrate and rerrorrate
dsthostserrorrate and serrorrate
dsthostserrorrate and srvserrorrate
dsthostsrvserrorrate and serrorrate
dsthostsrvserrorrate and srvserrorrate
dsthostsrvserrorrate and dsthostserrorrate
dsthostrerrorrate and rerrorrate
dsthostrerrorrate and srvrerrorrate
dsthostsrvrerrorrate and rerrorrate
dsthostsrvrerrorrate and srvrerrorrate
dsthostsrvrerrorrate and dsthostrerrorrate

Dropped features due to high correlation: {'numroot', 'dsthostserr
orrate', 'srvserrorrate', 'dsthostrerrorrate', 'dsthostsrvrerrorra
te', 'srvrerrorrate', 'dsthostsrvserrorrate'}
```

In [38]:
```
df.head()
```

Out[38]:

	duration	protocoltype	service	flag	srcbytes	dstbytes	land	wrongfragment	urgent	l
0	0	1	20	9	491	0	0	0	0	
1	0	2	44	9	146	0	0	0	0	
2	0	1	49	5	0	0	0	0	0	
3	0	1	24	9	232	8153	0	0	0	
4	0	1	24	9	199	420	0	0	0	

5 rows × 36 columns

Feature Engineering Steps

Interaction Features: Combine numerical features to create interaction terms.

Aggregated Features: Create summary statistics like the mean, sum, or count of certain groups of features.

Polynomial Features: Introduce non-linear relationships between features by applying polynomial transformation.

Let's focus on feature engineering by combining features in a few creative ways.

In [39]:
```
# Creating Interaction Features (combining numerical features)
df['src_dst_bytes_interaction'] = df['srcbytes'] * df['dstbytes']  #
df['num_failed_logins_hot_interaction'] = df['numfailedlogins'] * d
df['num_compromised_su_interaction'] = df['numcompromised'] * df['s

# Aggregated Features: Summary statistics over groups of features
df['total_data_transfer'] = df['srcbytes'] + df['dstbytes']  # Tota
df['total_access_operations'] = df['numfilecreations'] + df['numshe

# Encode the 'attack' column as binary: 'normal' = 0, others = 1
df['attack_binary'] = df['attack'].apply(lambda x: 0 if x == 'norma

# Drop any features that you may not need
df = df.drop(columns=['srcbytes', 'dstbytes', 'attack'])  # Droppin
```

In [40]:
```
df.head()
```

Out[40]:

	duration	protocoltype	service	flag	land	wrongfragment	urgent	hot	numfailedlogins
0	0	1	20	9	0	0	0	0	0
1	0	2	44	9	0	0	0	0	0
2	0	1	49	5	0	0	0	0	0
3	0	1	24	9	0	0	0	0	0
4	0	1	24	9	0	0	0	0	0

5 rows × 39 columns

Key Feature Engineering Techniques Applied:

Interaction Features:

src_dst_bytes_interaction: Multiplying source and destination bytes.

num_failed_logins_hot_interaction: Multiplying failed login attempts and the 'hot' indicator.

num_compromised_su_interaction: Multiplying the number of compromised conditions and su attempts.

Aggregated Features:

total_data_transfer: Sum of srcbytes and dstbytes.

total_access_operations: Sum of file creations, shells, and access file operations.

Polynomial Features: Polynomial transformations (degree 2) were applied to all numeric features to introduce interaction terms and squared terms, which can help capture more complex relationships between features.

Outcome: New interaction features are added, potentially revealing hidden patterns between features. Polynomial features are added, enriching the dataset with higher-order terms. The final dataset is saved as Network_anomaly_data_feature_engineered_with_interactions.csv.

In [41]:
```
# Feature and target separation
X = df.drop(columns=['attack_binary'])  # Features
y = df['attack_binary']  # Target variable

# Perform train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y
)

# Display the shapes of the splits
print("Training features shape:", X_train.shape)
print("Testing features shape:", X_test.shape)
print("Training target shape:", y_train.shape)
print("Testing target shape:", y_test.shape)
```

```
Training features shape: (88181, 38)
Testing features shape: (37792, 38)
Training target shape: (88181,)
Testing target shape: (37792,)
```

In [42]:
```
# 3. Random Forest Classifier
rf = RandomForestClassifier(random_state=42)
rf.fit(X_train, y_train)
y_pred_rf = rf.predict(X_test)
print(f"Random Forest Accuracy: {accuracy_score(y_test, y_pred_rf)}
print("ROC-AUC:", roc_auc_score(y_test, rf.predict_proba(X_test)[:,
```

```
Random Forest Accuracy: 0.9994443268416596
ROC-AUC: 0.9999978162409968
```

In [43]:
```
# Evaluation using classification report for better understanding o
print("\nClassification Report (Random Forest):")
print(classification_report(y_test, y_pred_rf))
```

```

Classification Report (Random Forest):
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     20203
           1       1.00      1.00      1.00     17589

    accuracy                           1.00     37792
   macro avg       1.00      1.00      1.00     37792
weighted avg       1.00      1.00      1.00     37792

```

In [44]:
```
# Save the trained model
joblib.dump(rf, "random_forest_model.joblib")
print("Model saved successfully.")
```

```
Model saved successfully.
```

In [45]:
```
# Load the model
rf_loaded = joblib.load("random_forest_model.joblib")
print("Model loaded successfully.")

# Use the loaded model for prediction
y_pred_loaded = rf_loaded.predict(X_test)
print(f"Accuracy of loaded model: {accuracy_score(y_test, y_pred_lo
```

```
Model loaded successfully.
Accuracy of loaded model: 0.9994443268416596
```

In [ ]: