In [57]:
```
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, GradientBoostir
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
```

In [58]:
```
# Suppress warnings
warnings.filterwarnings("ignore")
```

In [59]:
```
# 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 [60]:
```
# 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 [61]:
```
# 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 [62]:
```
# 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
```

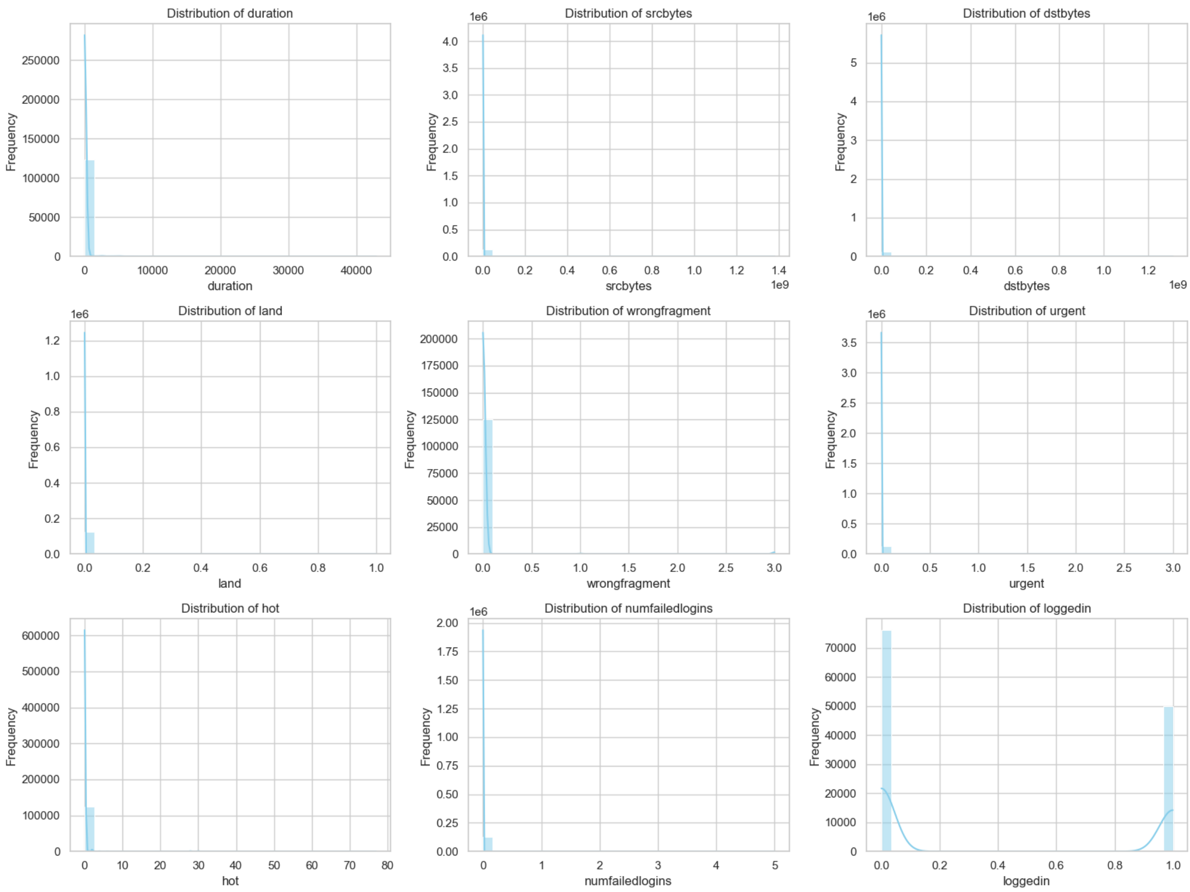
In [63]:
```
# Set plot style
sns.set(style="whitegrid")

# 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:

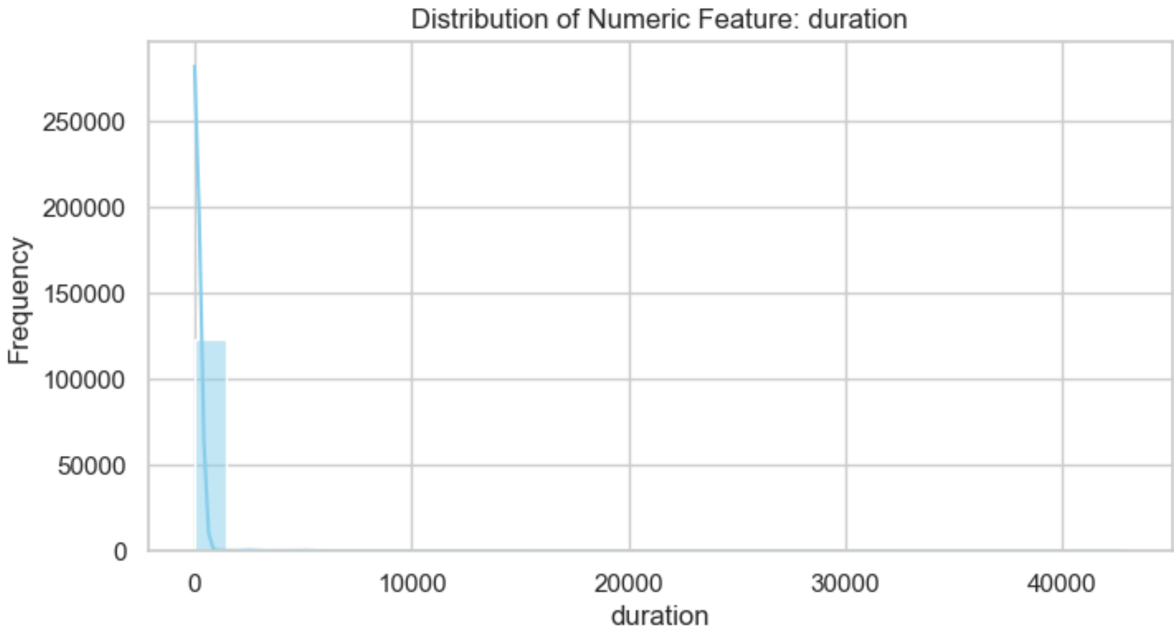
Features like duration, srcbytes, and dstbytes have highly skewed distributions, likely influenced by extreme outliers or infrequent high values. Binary features such as land and urgent show a discrete distribution. Some features, like wrongfragment, have a significant number of zero entries, indicating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

In [64]:
```
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 [65]:
```
# Call the function to visualize all feature distributions
plot_distributions(df)
```



Corelation

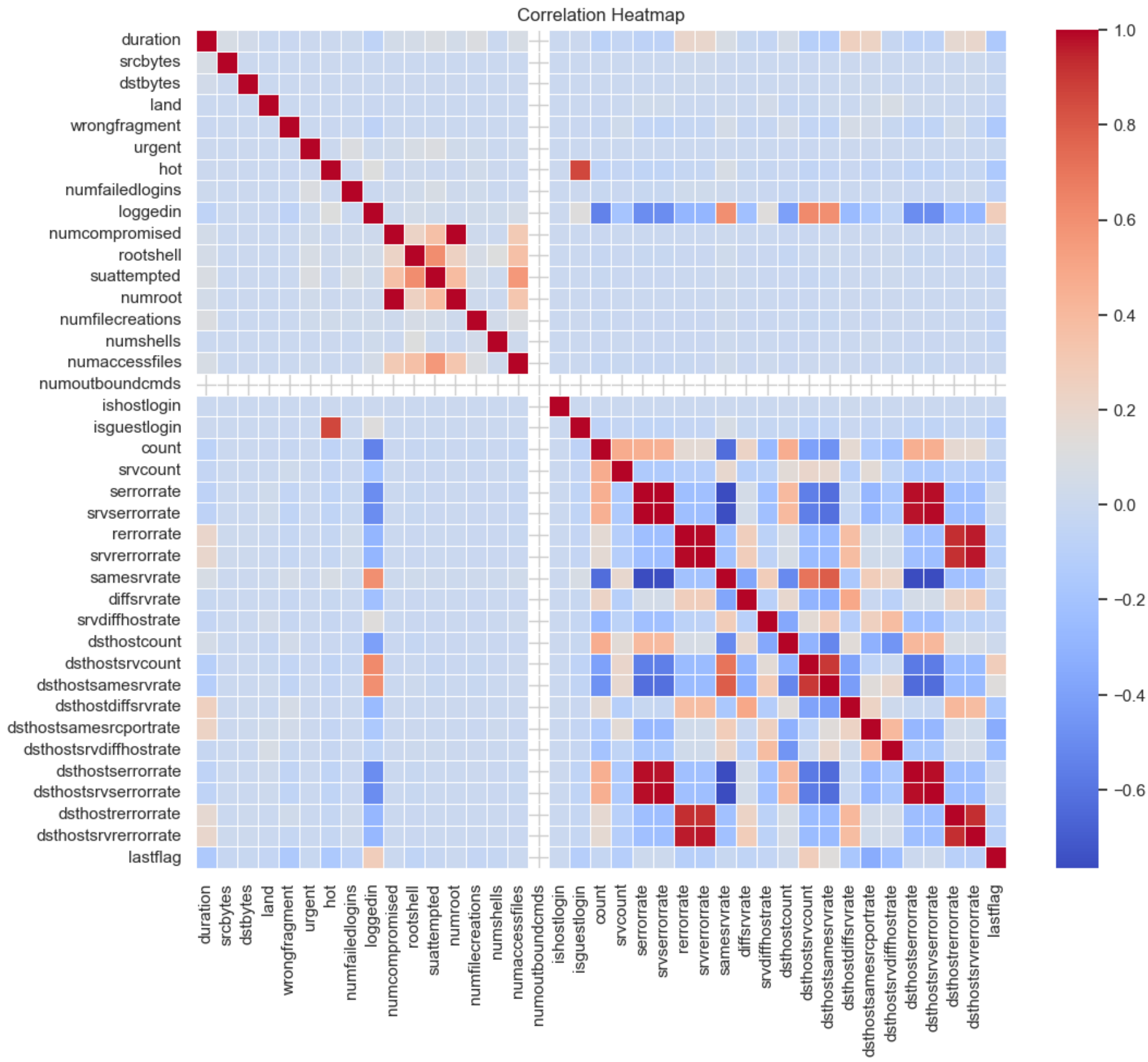
To identify highly correlated features in your dataset and drop the ones that are redundant, we can calculate the correlation matrix and use a threshold to decide which features to drop.

In [66]:
```
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 [67]:
```
# Call the function for correlation analysis
correlation_matrix = correlation_analysis(df)
```



In [68]:
```
# 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 [69]:
```
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())
```

```
Mapping for protocoltype:
  0 -> icmp
  1 -> tcp
  2 -> udp

Mapping for service:
  0 -> IRC
  1 -> X11
  2 -> Z39_50
  3 -> aol
  4 -> auth
  5 -> bgp
  6 -> courier
  7 -> csnet_ns
  8 -> ctf
  9 -> daytime
  10 -> discard
  11 -> domain
  12 -> domain_u
```

Explanation:

Correlation Matrix: df.corr() computes the pairwise correlation of columns in the dataset. It only applies to numerical columns.

Threshold: A threshold (e.g., 0.9) is used to identify features that are highly correlated. You can adjust this value based on your needs.

Iterative Check: For each pair of features, if the correlation exceeds the threshold, one of the features is added to the correlated_features set.

Feature Dropping: The features in correlated_features are dropped from the dataset.

Output: The code prints the names of the dropped features and saves the updated dataset to a new file.

In [70]:
```
# 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 [ ]:
```
# 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
```

In [72]:
```
df.head()
```

Out[72]:

	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.

In [73]:
```
# 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 [74]:
```
df.head()
```

Out[74]:

	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 [75]:
```
# 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,)
```

1. Logistic Regression

In [76]:
```
# 1. Logistic Regression
log_reg = LogisticRegression(max_iter=1000)
log_reg.fit(X_train, y_train)
y_pred_log_reg = log_reg.predict(X_test)
print(f"Logistic Regression Accuracy: {accuracy_score(y_test, y_pre
print("ROC-AUC:", roc_auc_score(y_test, log_reg.predict_proba(X_tes
```

```
Logistic Regression Accuracy: 0.5345840389500424
ROC-AUC: 0.5
```

2. Decision Tree Classifier

In [77]:
```
# 2. Decision Tree Classifier
dt = DecisionTreeClassifier(random_state=42)
dt.fit(X_train, y_train)
y_pred_dt = dt.predict(X_test)
print(f"Decision Tree Accuracy: {accuracy_score(y_test, y_pred_dt)}
print("ROC-AUC:", roc_auc_score(y_test, dt.predict_proba(X_test)[:,
```

```
Decision Tree Accuracy: 0.9983329805249789
ROC-AUC: 0.9983084155315277
```

3. Random Forest Classifier

In [78]:
```
# 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
```

4. Support Vector Machine (SVM)

In [79]:
```
# 4. Support Vector Machine (SVM)
svm = SVC(random_state=42)
svm.fit(X_train, y_train)
y_pred_svm = svm.predict(X_test)
print(f"SVM Accuracy: {accuracy_score(y_test, y_pred_svm)}")
```

```
SVM Accuracy: 0.5345840389500424
```

5. Neural Network (MLP Classifier)

In [80]:
```
# 5. Neural Network (MLP Classifier)
mlp = MLPClassifier(hidden_layer_sizes=(100,), max_iter=500, random
mlp.fit(X_train, y_train)
y_pred_mlp = mlp.predict(X_test)
print(f"Neural Network Accuracy: {accuracy_score(y_test, y_pred_mlp
print("ROC-AUC:", roc_auc_score(y_test, mlp.predict_proba(X_test)[:
```

```
Neural Network Accuracy: 0.9621613039796783
ROC-AUC: 0.9790412899495952
```

Ensemble Methods

1. Gradient Boosting (Boosting)

In [81]:
```

gb = GradientBoostingClassifier(random_state=42)
gb.fit(X_train, y_train)
y_pred_gb = gb.predict(X_test)
print(f"Gradient Boosting Accuracy: {accuracy_score(y_test, y_pred_
print("ROC-AUC:", roc_auc_score(y_test, gb.predict_proba(X_test)[:,
```

```
Gradient Boosting Accuracy: 0.9971422523285352
ROC-AUC: 0.9999696539108097
```

2. Bagging Classifier

In [82]:
```
# 2. Bagging Classifier
bagging = BaggingClassifier(random_state=42)
bagging.fit(X_train, y_train)
y_pred_bagging = bagging.predict(X_test)
print(f"Bagging Accuracy: {accuracy_score(y_test, y_pred_bagging)}"
print("ROC-AUC:", roc_auc_score(y_test, bagging.predict_proba(X_tes
```

```
Bagging Accuracy: 0.9991797205757832
ROC-AUC: 0.9999389968610912
```

3. Stacking Classifier (Using Logistic Regression, Random Forest, and SVM)

In [83]:
```
# 3. Stacking Classifier (Using Logistic Regression, Random Forest,
stacking = VotingClassifier(estimators=[
    ('log_reg', log_reg),
    ('rf', rf),
    ('svm', svm)
], voting='hard')
stacking.fit(X_train, y_train)
y_pred_stacking = stacking.predict(X_test)
print(f"Stacking Accuracy: {accuracy_score(y_test, y_pred_stacking)
```

```
Stacking Accuracy: 0.5345840389500424
```

Model Evaluation:

Accuracy: Measures the percentage of correct predictions.

Classification Report: Includes precision, recall, and F1-score for each class, which gives a better understanding of how the model performs across different classes.

Cross-validation: The code uses train_test_split for a basic train-test split, but you can also apply cross-validation (e.g., cross_val_score) for more robust performance evaluation.

In [84]:
```
# Evaluation using classification report for better understanding o
print("\nClassification Report (Logistic Regression):")
print(classification_report(y_test, y_pred_log_reg))

print("\nClassification Report (Decision Tree):")
print(classification_report(y_test, y_pred_dt))

print("\nClassification Report (Random Forest):")
```

```
print(classification_report(y_test, y_pred_rf))

print("\nClassification Report (SVM):")
print(classification_report(y_test, y_pred_svm))

print("\nClassification Report (Neural Network):")
print(classification_report(y_test, y_pred_mlp))

print("\nClassification Report (Gradient Boosting):")
print(classification_report(y_test, y_pred_gb))

print("\nClassification Report (Bagging):")
print(classification_report(y_test, y_pred_bagging))

print("\nClassification Report (Stacking):")
print(classification_report(y_test, y_pred_stacking))
```

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

           0       0.53      1.00      0.70     20203
           1       0.00      0.00      0.00     17589

    accuracy                           0.53     37792
   macro avg       0.27      0.50      0.35     37792
weighted avg       0.29      0.53      0.37     37792


Classification Report (Decision Tree):
              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


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


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

```
           0       0.53      1.00      0.70     20203
           1       0.00      0.00      0.00     17589

    accuracy                           0.53     37792
   macro avg       0.27      0.50      0.35     37792
weighted avg       0.29      0.53      0.37     37792


Classification Report (Neural Network):
              precision    recall  f1-score   support

           0       0.96      0.97      0.96     20203
           1       0.96      0.96      0.96     17589

    accuracy                           0.96     37792
   macro avg       0.96      0.96      0.96     37792
weighted avg       0.96      0.96      0.96     37792


Classification Report (Gradient Boosting):
              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


Classification Report (Bagging):
              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


Classification Report (Stacking):
              precision    recall  f1-score   support

           0       0.53      1.00      0.70     20203
           1       0.00      0.00      0.00     17589

    accuracy                           0.53     37792
   macro avg       0.27      0.50      0.35     37792
weighted avg       0.29      0.53      0.37     37792
```

In [88]:
```
models = {
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'Random Forest': RandomForestClassifier(n_estimators=100, rando
    'Gradient Boosting': GradientBoostingClassifier(random_state=42
    'XGBoost': XGBClassifier(use_label_encoder=False, eval_metric='
}

# k-Fold Cross-Validation
k = 5  # Number of folds
kf = KFold(n_splits=k, shuffle=True, random_state=42)

# Evaluate each model
results = {}
for model_name, model in models.items():
    print(f"Evaluating {model_name}...")
    scores = cross_val_score(model, X, y, cv=kf, scoring='accuracy'
    results[model_name] = {
        'Mean Accuracy': scores.mean(),
        'Std Dev': scores.std()
    }

# Display results
results_df = pd.DataFrame(results).T
print("\nCross-Validation Results:")
print(results_df)
```

```
Evaluating Decision Tree...
Evaluating Random Forest...
Evaluating Gradient Boosting...
Evaluating XGBoost...

Cross-Validation Results:
                   Mean Accuracy   Std Dev
Decision Tree           0.998690  0.000112
Random Forest           0.999460  0.000228
Gradient Boosting       0.997230  0.000423
XGBoost                 0.999476  0.000136
```

Voting Classifier Ensemble:

The idea is to combine all the models into a single meta-model using hard voting (majority voting) or soft voting (probability averaging). Once combined, the model with the highest accuracy or best performance can be chosen based on evaluation metrics.

We will use VotingClassifier from sklearn to ensemble the models. After training, we'll compare all models' performance, and you can choose the best one based on metrics like accuracy, F1-score, or ROC-AUC.

In [89]:
```
# Define individual models
log_reg = LogisticRegression(max_iter=1000, random_state=42)
```

```
dt = DecisionTreeClassifier(random_state=42)
rf = RandomForestClassifier(random_state=42)
svm = SVC(random_state=42)
mlp = MLPClassifier(hidden_layer_sizes=(100,), max_iter=500, random
gb = GradientBoostingClassifier(random_state=42)
bagging = BaggingClassifier(random_state=42)

# Create a Voting Classifier (soft voting to average probabilities)
voting_clf = VotingClassifier(estimators=[
    ('log_reg', log_reg),
    ('dt', dt),
    ('rf', rf),
    ('svm', svm),
    ('mlp', mlp),
    ('gb', gb),
    ('bagging', bagging)
], voting='hard')  # Use 'hard' for majority voting, 'soft' for pro

# Train the ensemble model
voting_clf.fit(X_train, y_train)

# Evaluate the performance of the ensemble
y_pred_voting = voting_clf.predict(X_test)
print(f"Voting Classifier Accuracy: {accuracy_score(y_test, y_pred_
print("\nClassification Report (Voting Classifier):")
print(classification_report(y_test, y_pred_voting))

# Now compare individual models
models = [log_reg, dt, rf, svm, mlp, gb, bagging]
model_names = ['Logistic Regression', 'Decision Tree', 'Random Fore

# Evaluate and print the accuracy of each individual model
for model, name in zip(models, model_names):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    print(f"{name} Accuracy: {accuracy_score(y_test, y_pred)}")
    print(f"Classification Report for {name}:")
    print(classification_report(y_test, y_pred))

# Evaluate using Cross-validation
cv_scores = []
for model, name in zip(models, model_names):
    cv_score = cross_val_score(model, X, y, cv=5, scoring='accuracy
    cv_scores.append((name, cv_score))

# Display the cross-validation results for all models
cv_scores.sort(key=lambda x: x[1], reverse=True)
print("\nCross-validation results:")
for name, score in cv_scores:
    print(f"{name}: {score:.4f}")

# Choose the best model based on accuracy or F1-score (you can modi
best_model_name = cv_scores[0][0]
```

```
print(f"\nBest Model based on cross-validation performance: {best_m
```

```
Voting Classifier Accuracy: 0.998756350550381

Classification Report (Voting Classifier):
              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

Logistic Regression Accuracy: 0.5345840389500424
Classification Report for Logistic Regression:
              precision    recall  f1-score   support

           0       0.53      1.00      0.70     20203
           1       0.00      0.00      0.00     17589

    accuracy                           0.53     37792
   macro avg       0.27      0.50      0.35     37792
weighted avg       0.29      0.53      0.37     37792

Decision Tree Accuracy: 0.9983329805249789
Classification Report for Decision Tree:
              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

Random Forest Accuracy: 0.9994443268416596
Classification Report for 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

SVM Accuracy: 0.5345840389500424
Classification Report for SVM:
              precision    recall  f1-score   support

           0       0.53      1.00      0.70     20203
           1       0.00      0.00      0.00     17589
```

```
    accuracy                           0.53     37792
   macro avg       0.27      0.50      0.35     37792
weighted avg       0.29      0.53      0.37     37792

Neural Network Accuracy: 0.9621613039796783
Classification Report for Neural Network:
              precision    recall  f1-score   support

           0       0.96      0.97      0.96     20203
           1       0.96      0.96      0.96     17589

    accuracy                           0.96     37792
   macro avg       0.96      0.96      0.96     37792
weighted avg       0.96      0.96      0.96     37792

Gradient Boosting Accuracy: 0.9971422523285352
Classification Report for Gradient Boosting:
              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

Bagging Accuracy: 0.9991797205757832
Classification Report for Bagging:
              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


Cross-validation results:
Random Forest: 0.9995
Bagging: 0.9991
Decision Tree: 0.9987
Gradient Boosting: 0.9973
Neural Network: 0.9595
Logistic Regression: 0.5346
SVM: 0.5346

Best Model based on cross-validation performance: Random Forest
```

Explanation:

Voting Classifier:

The VotingClassifier combines all the models using majority voting (hard voting) or probability averaging (soft voting). Here, we're using hard voting for a majority decision, but you can change it to soft for probabilistic averaging.

Training & Testing: Each individual model (Logistic Regression, Decision Tree, Random Forest, SVM, Neural Network, Gradient Boosting, and Bagging) is trained and tested separately.

Cross-validation:

We evaluate the performance of each model using cross-validation (cross_val_score) to get a more reliable estimate of their accuracy. The cross-validation results are sorted, and the best model is chosen.

Choosing the Best Model: Based on the cross-validation accuracy, the best model is selected. You can customize this selection process based on metrics like F1-score or ROC-AUC if needed.

Output:

The script will print the accuracy and classification report for each individual model and the ensemble model.

The cross-validation results will help in selecting the best model based on the highest average accuracy.

In [ ]: