

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# For feature selection
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectFromModel

# For statistical analysis
from scipy import stats
```

```
df=pd.read_csv('file1.csv')
df
```




	time	device_address	physical_payload	gateway	crc_status	fi
0	2019-03-01T00:00:01.528887066Z	01ae0905	QAUJrgGA3CIF/9yXgSG9G2+SwnOEzEmlHJeTCuE=	00000f0c210721f2	1	86
1	2019-03-01T00:00:01.528930845Z	01ae0905	QAUJrgGA3CIF/9yXgSG9G2+SwnOEzEmlHJeTCuE=	00000f0c210721f2	1	86
2	2019-03-01T00:00:01.822131604Z	00c2d5cc	QMzVwgCA7xoFASIHknHqtrHhvTB4DvnUz/HSvs=	00000f0c210721f2	1	86
3	2019-03-01T00:00:01.822184581Z	00c2d5cc	QMzVwgCA7xoFASIHknHqtrHhvTB4DvnUz/HSvs=	00000f0c210721f2	1	86
4	2019-03-01T00:00:03.924795694Z	-1	NaN	00000f0c210721f2	-1	86
...	...	...	...	...	...	...
108420	2019-03-01T23:59:43.726314706Z	10003432	QDI0ABCAug8BmDSRJF3Vv8eR3OH07twjPyKrX0tcqtwB2...	00000f0c22433141	1	86
108421	2019-03-01T23:59:56.371057987Z	-1	NaN	00000f0c22433141	-1	86
108422	2019-03-01T23:58:19.264275Z	fa2dd4c4	m8TULfqX/aTLvbsiRvo/jATE+0RiCFoQ2UC8lxemOLVRn...	00800000a0001793	-1	86
108423	2019-03-01T23:57:25.821769386Z	8e98fc05	ewX8ml6/wjnOKqoazwPuba7eeRp+o9fZ7jNLZkRhKh/Pp8...	00800000a0001914	-1	86
108424	2019-03-01T23:58:01.389385243Z	e04f2714	fBQnT+C46c+bkOilfuCJUzH6MKwg+xHjPh2USgv+67U3nd...	00800000a0001914	-1	86

108425 rows × 15 columns



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```
print(df.describe())
```



	crc_status	frequency	spreading_factor	bandwidth	\
count	108425.000000	1.084250e+05	108424.000000	108424.000000	
mean	0.359041	8.681482e+08	7.986433	125.547619	
std	0.933326	3.567392e+05	0.916765	8.255487	
min	-1.000000	8.671000e+08	7.000000	125.000000	
25%	-1.000000	8.681000e+08	7.000000	125.000000	
50%	1.000000	8.681000e+08	8.000000	125.000000	
75%	1.000000	8.685000e+08	8.000000	125.000000	
max	1.000000	8.688000e+08	12.000000	250.000000	

	rssI	snr	size	mtype	\
count	108425.000000	108425.000000	108425.000000	108425.000000	
mean	-108.471312	-6.161835	21.315822	8.812184	
std	6.019582	6.129328	19.387354	15.755465	
min	-123.000000	-128.000000	0.000000	-1.000000	
25%	-113.000000	-11.000000	0.000000	-1.000000	
50%	-109.000000	-7.000000	29.000000	10.000000	
75%	-105.000000	-2.000000	29.000000	10.000000	
max	-68.000000	15.000000	255.000000	111.000000	

	fcnt	fport
count	108425.000000	108391.000000
mean	9802.214628	4.006467
std	13504.482517	13.112764
min	-1.000000	-1.000000

```

25%      -1.000000      -1.000000
50%      5691.000000      5.000000
75%      10554.000000      5.000000
max       65461.000000     255.000000

```

```
# df['time'] = pd.to_datetime(df['time']).astype('int64') // 10**9
```

```
# print(df['time'])
```

```

0      1551398401
1      1551398401
2      1551398401
3      1551398401
4      1551398403
...
108420  1551484783
108421  1551484796
108422  1551484699
108423  1551484645
108424  1551484681
Name: time, Length: 108425, dtype: int64

```

```

numeric_cols = df.select_dtypes(include='number').columns
print(numeric_cols)

```

```

Index(['crc_status', 'frequency', 'spreading_factor', 'bandwidth', 'rssi',
      'snr', 'size', 'mtype', 'fcnt', 'fport'],
      dtype='object')

```

```

selected_cols = numeric_cols.unique()
numeric_df = df[selected_cols]
numeric_df

```

```

0      1  868500000      8.0  125.0 -112  0.0  29  10  8924  5.0
1      1  868500000      8.0  125.0 -113 -9.0  29  10  8924  5.0
2      1  868100000      8.0  125.0 -108  2.0  29  10  6895  5.0
3      1  868100000      8.0  125.0 -101  9.0  29  10  6895  5.0
4     -1  868100000      8.0  125.0 -112 -11.0  0  -1  -1  -1.0
...
108420  1  868500000      7.0  125.0 -115 -7.0  42  10  4026  1.0
108421 -1  868100000      8.0  125.0 -116 -13.5  0  -1  -1  -1.0
108422 -1  867700000      7.0  125.0 -114 -10.8  47  100  63071  254.0
108423 -1  867300000      7.0  125.0 -111 -11.0  71  11  14786  217.0
108424 -1  867300000      7.0  125.0 -111 -11.5  168  11  53225  49.0

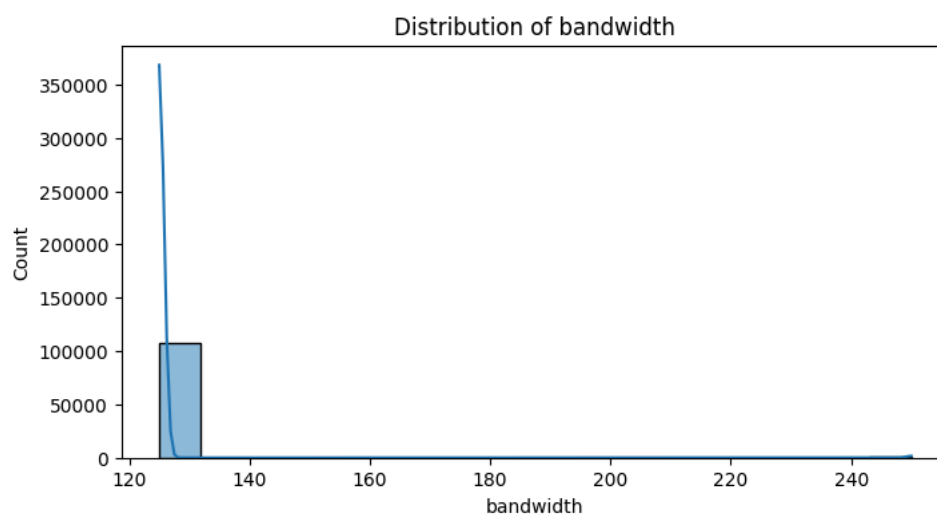
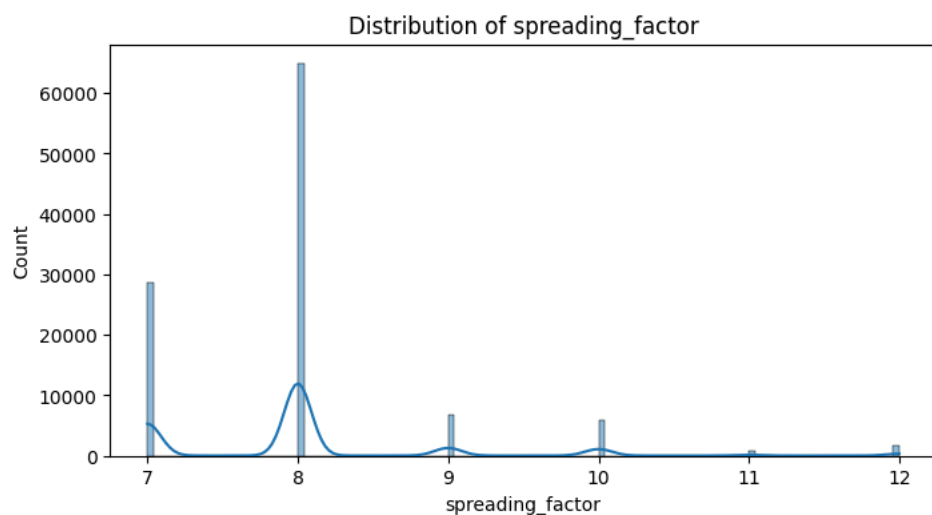
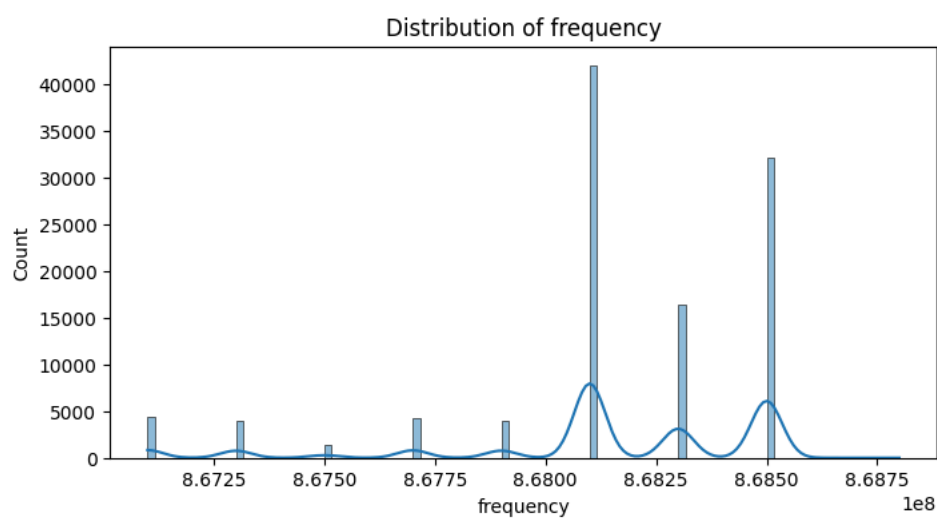
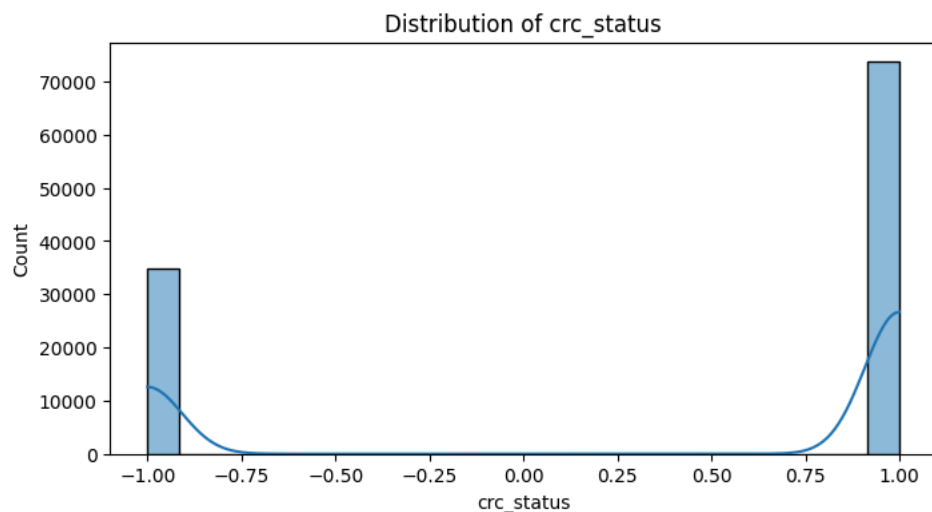
```

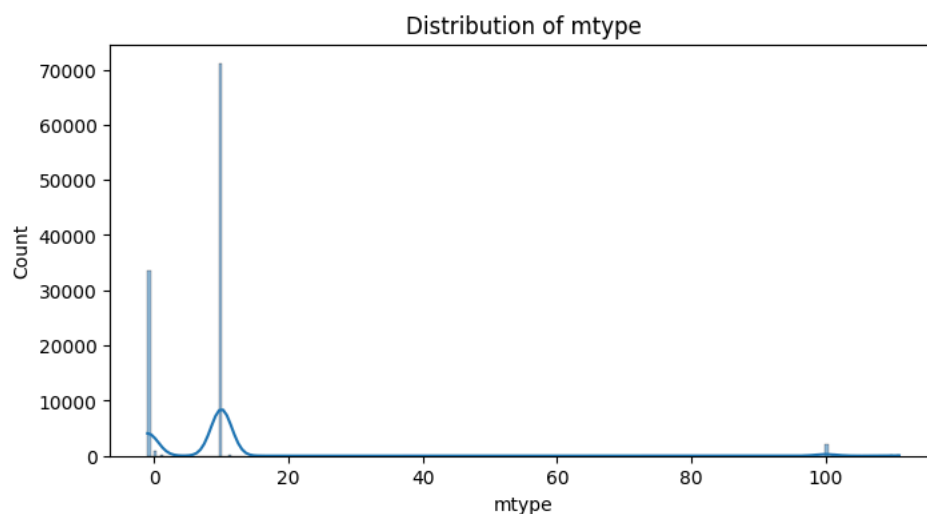
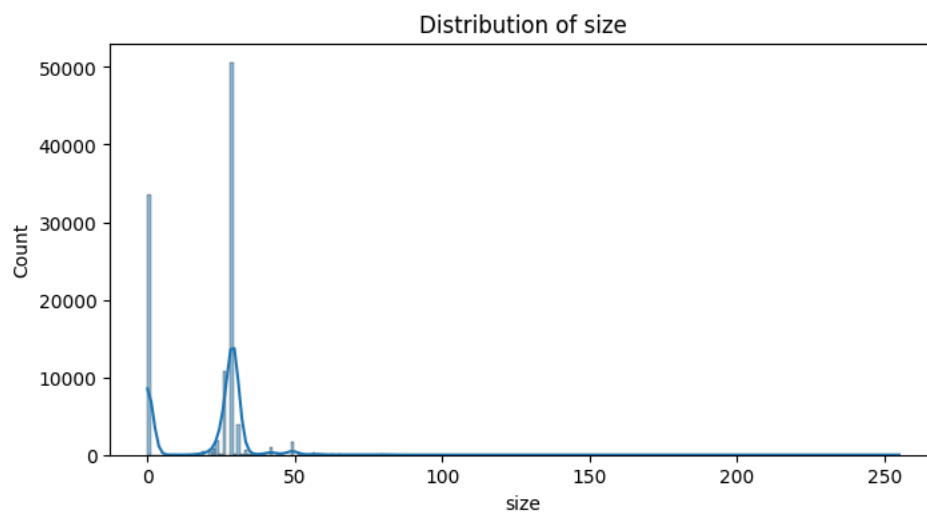
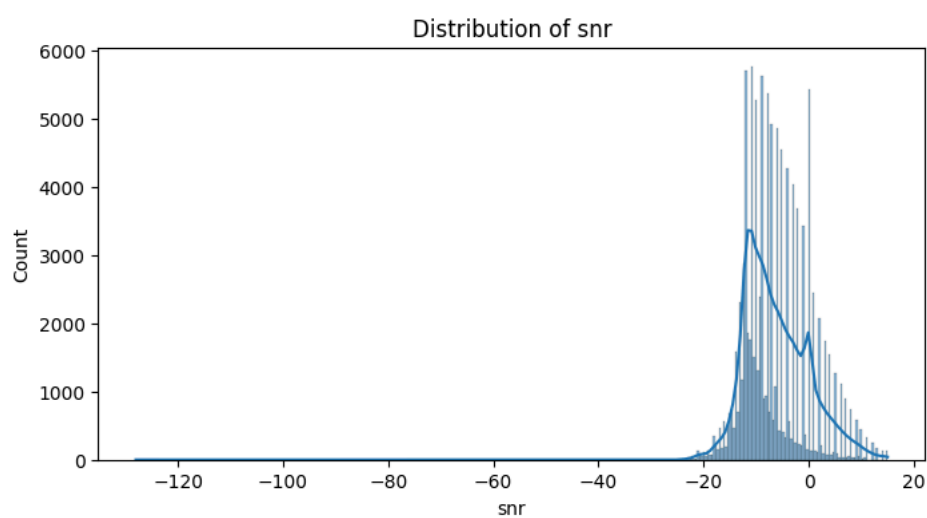
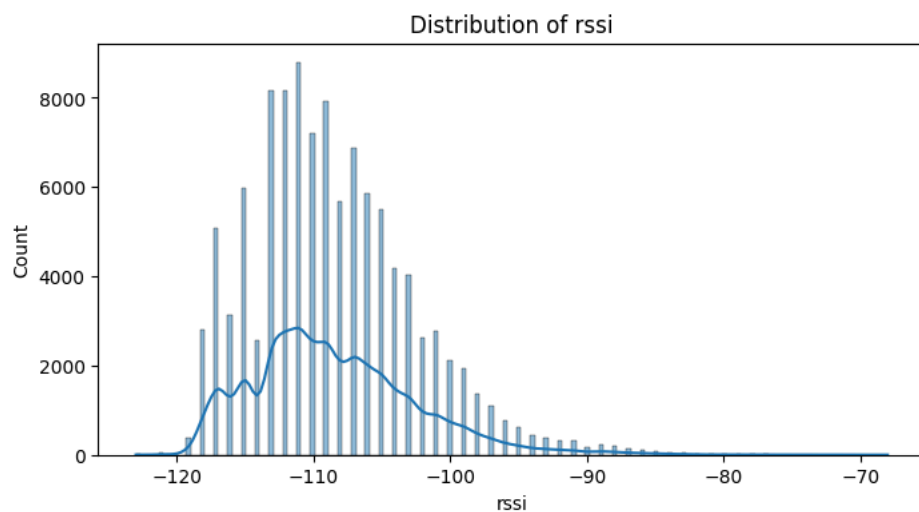
108425 rows x 10 columns

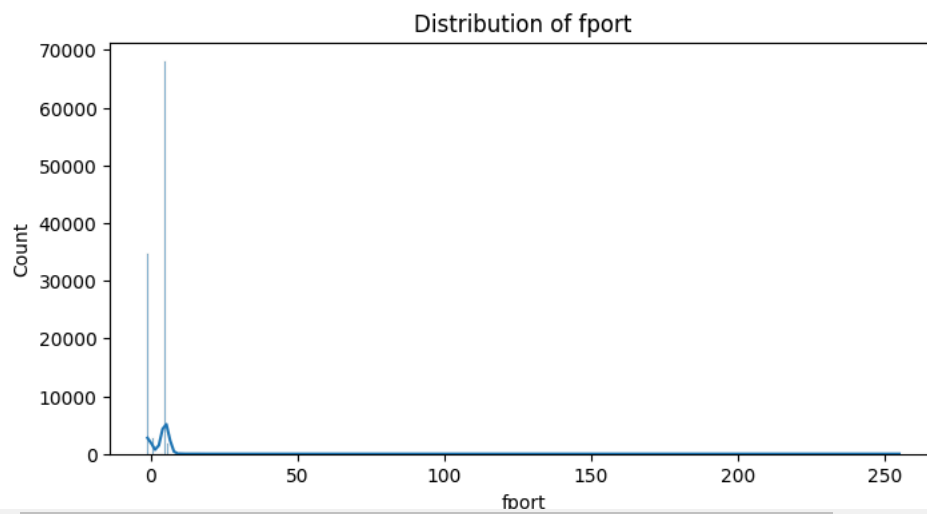
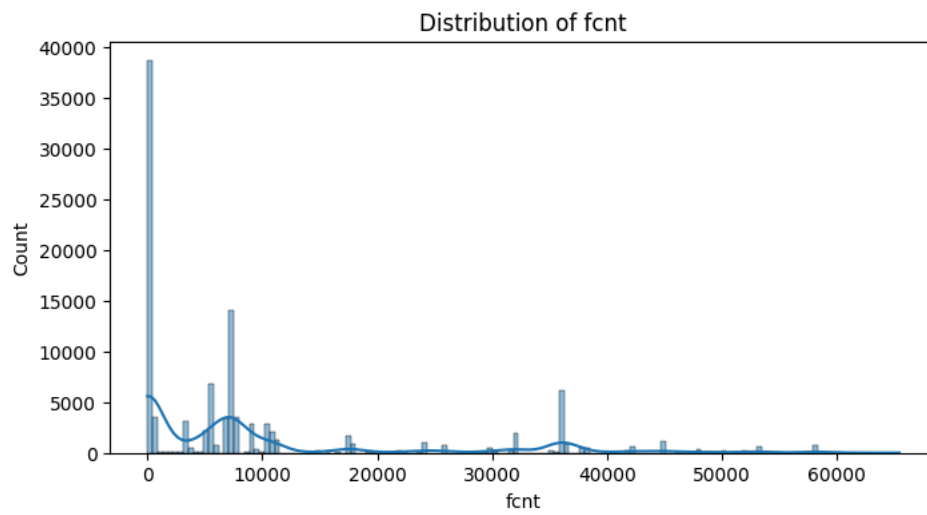
```

# Histograms for numerical features
for col in numeric_df:
    plt.figure(figsize=(8, 4))
    sns.histplot(df[col], kde=True)
    plt.title(f'Distribution of {col}')
    plt.show()

```

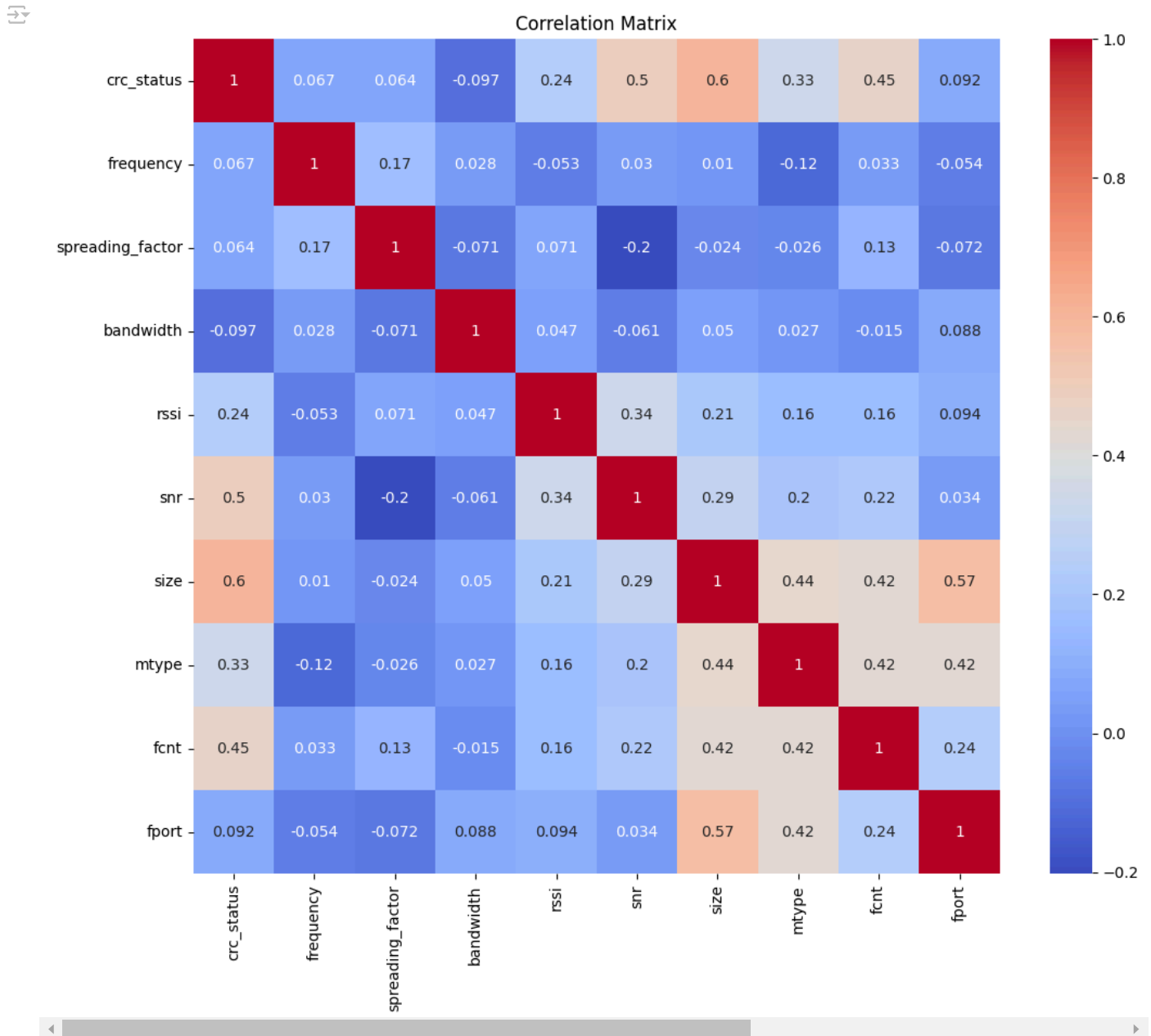






```
corr_matrix = numeric_df.corr()

# Plot heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
```

```
# Specify your features and target
features = ['frequency', 'spreading_factor', 'bandwidth', 'rssi', 'snr', 'size', 'mtype', 'fcnt', 'fport']
target = 'crc_status'
```

```
X = df[features]
y = df[target]
```

```
# Handle categorical variables
X = pd.get_dummies(X, columns=['mtype'], drop_first=True)
```

```
# Split data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```


```
# Create and fit the model
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)

# Get feature importances
importances = model.feature_importances_
feature_importances = pd.DataFrame({'feature': X.columns, 'importance': importances})
feature_importances = feature_importances.sort_values(by='importance', ascending=False)


# Select top N features
top_n = 3
best_features = feature_importances.head(top_n)['feature'].tolist()

print("Best features selected:", best_features)

# # Final DataFrame with selected features and target
# X_final = numeric_df[best_features + [target]]
```

 Best features selected: ['size', 'fport', 'fcnt']

```
# Final DataFrame with selected features and target
X_final = numeric_df[best_features + [target]]
X_final
```



	size	fport	fcnt	crc_status
0	29	5.0	8924	1
1	29	5.0	8924	1
2	29	5.0	6895	1
3	29	5.0	6895	1
4	0	-1.0	-1	-1
...	...	...	...	...
108420	42	1.0	4026	1
108421	0	-1.0	-1	-1
108422	47	254.0	63071	-1
108423	71	217.0	14786	-1