installing libraries

```
!pip install ucimlrepo
!pip install seaborn
!pip install matplotlib
```

Show hidden output

Importing Libraries

```
from ucimlrepo import fetch_ucirepo
import seaborn as sns
import matplotlib.pyplot as plt
from imblearn.over_sampling import RandomOverSampler
from sklearn.preprocessing import StandardScaler
import pandas as pd
import copy
```

fetching dataframe

```
magicGammaMain = fetch_ucirepo(id=159)
```

Creating copy of the dataframe

```
magicGamma = copy.deepcopy(magicGammaMain)
```

encoding target values

```
mgdf = magicGamma.data.original
X = magicGamma.data.features
y = magicGamma.data.targets
mgdf["class"] = mgdf["class"].map(lambda x: 1 if x == "g" else 0)
y = y.map(lambda x: 1 if x == "g" else 0)
```

Standardizing data

```
features_cols = mgdf.drop(columns=["class"]).columns
scaler = StandardScaler()
mgdf[features_cols] = scaler.fit_transform(mgdf[features_cols])
X[:] = scaler.transform(X)
```

describing data

```
print("Features shape",X.shape)
print("Target shape",y.shape)
mgdf.describe()
```

```
Features shape (19020, 10)
Target shape (19020, 1)
```

	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	
count	1.902000e+04	1.902000e+04	1.902000e+04	1.902000e+04	1.902000e+04	1.902000e+04	1.902000e+04	1.902000e+04	1.9
mean	7.172671e-17	-1.195445e-16	-2.241460e-16	-3.025971e-16	1.128201e-16	-5.977226e-18	4.184058e-17	-9.712992e-18	1.
std	1.000026e+00	1.000026e+00	1.000026e+00	1.000026e+00	1.000026e+00	1.000026e+00	1.000026e+00	1.000026e+00	1.0
min	-1.155862e+00	-1.209064e+00	-1.869959e+00	-2.008809e+00	-1.939745e+00	-7.661315e+00	-6.712427e+00	-9.897993e+00	-1.0
25%	-6.825213e-01	-5.623790e-01	-7.361978e-01	-7.905934e-01	-7.798731e-01	-2.745535e-01	-4.586055e-01	-5.329216e-01	-8.
50%	-3.800999e-01	-2.747838e-01	-1.807437e-01	-1.431941e-01	-1.643062e-01	1.409487e-01	9.350332e-02	1.999694e-02	-3.
75%	3.982656e-01	1.394619e-01	5.852541e-01	6.748758e-01	6.385776e-01	4.796163e-01	4.959385e-01	5.136004e-01	6.
max	6.631304e+00	1.276608e+01	5.286407e+00	2.804429e+00	4.167511e+00	9.789330e+00	4.466292e+00	8.623528e+00	2.3

```
mgdf
```

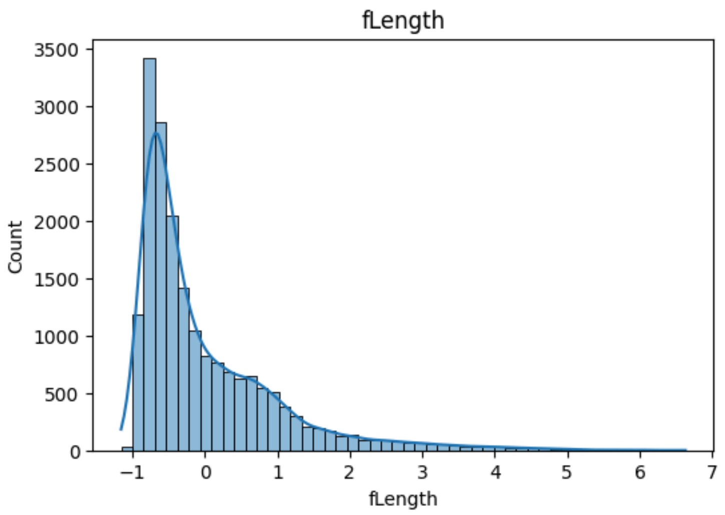
	fLength	fWidth	fSize	fConc	fConc1	fAsym	fM3Long	fM3Trans	fAlpha	fDist	class
0	-0.577226	-0.336804	-0.381130	0.062759	-0.148923	0.541042	0.224818	-0.405842	0.476816	-1.497866	1
1	-0.510969	-0.570027	-0.648595	0.820383	1.471776	0.516919	0.260364	-0.490094	-0.815418	0.153125	1
2	2.568278	6.205858	2.615783	-1.875883	-1.773241	2.044992	-1.478536	-2.183030	1.889224	0.842635	1
3	-0.694768	-0.687259	-1.029478	1.282069	1.606608	0.532771	-0.333515	-0.355359	-0.658804	-1.031463	1
4	0.516622	0.476384	0.711157	-0.347506	-0.284660	-0.020200	0.353086	1.036620	-0.881039	2.176427	1
...	...	...	...	...	...	...	...	...	...	...	...
19015	-0.752189	-0.613988	-0.442072	1.123433	1.617467	0.330947	0.019196	0.126129	-0.966282	-1.164090	0
19016	-0.573721	-0.843744	-1.180350	0.846640	0.576817	0.699497	0.051761	-0.154268	2.266097	0.717759	0
19017	0.523923	1.381779	1.318877	-1.305340	-1.445663	-0.084864	0.598262	-0.466509	0.101636	0.839003	0
19018	1.587757	2.982781	2.473375	-1.564081	-1.324404	0.171204	-2.040597	-3.077206	2.185260	2.870321	0
19019	3.161459	1.679993	0.813149	-0.507237	-0.549799	-2.752844	-3.509914	1.499301	0.961014	1.050442	0

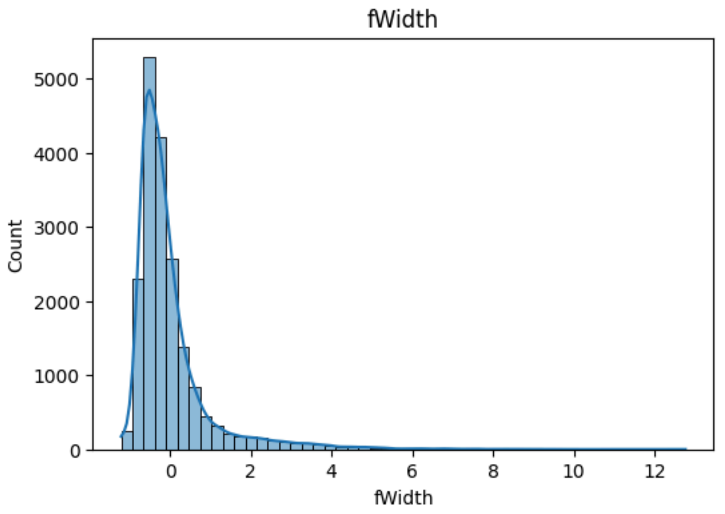
19020 rows × 11 columns

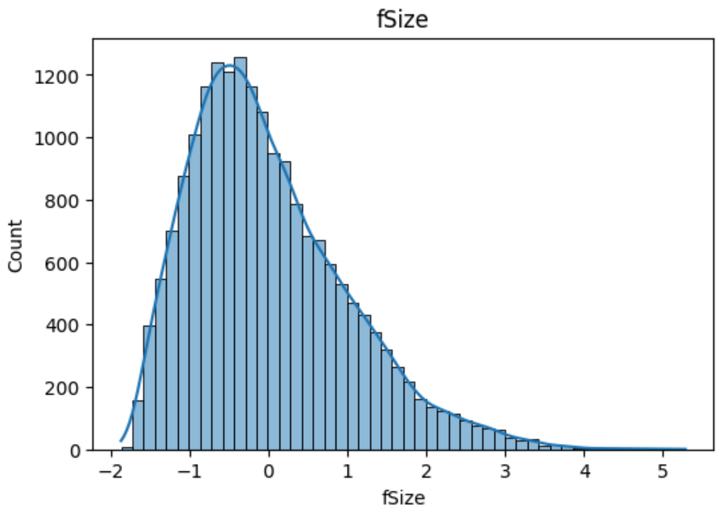
Next steps: Generate code with mgdf New interactive sheet

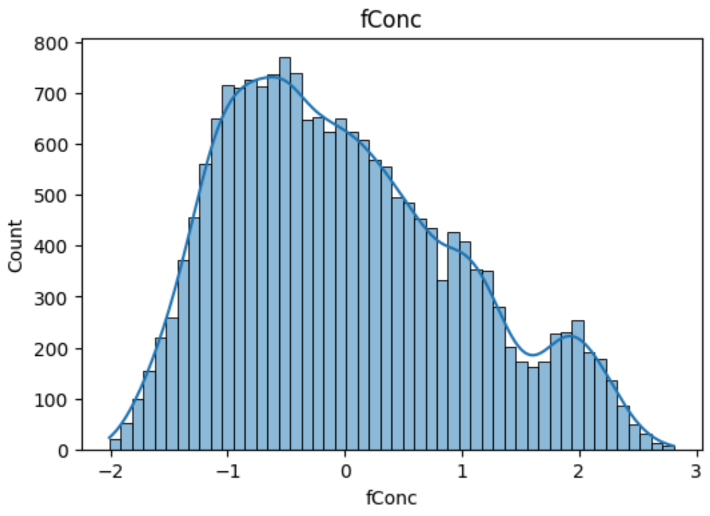
Plotting hisplot of features

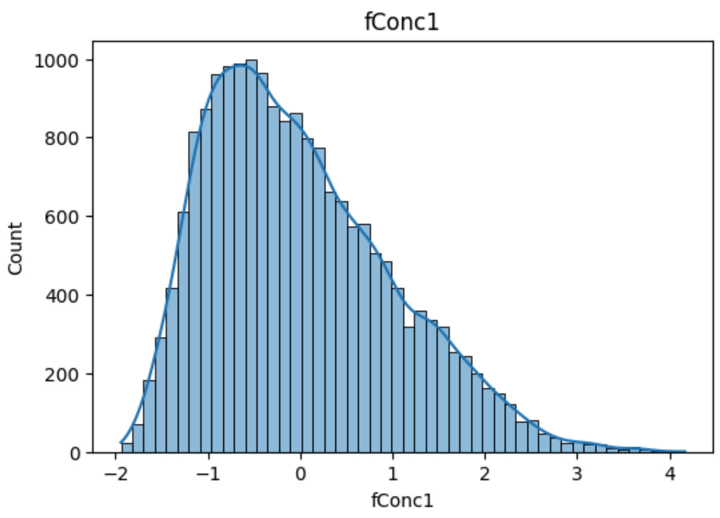
```
for col in features_cols:
    plt.figure(figsize=(6, 4))
    sns.histplot(mgdf[col], bins=50, kde=True)
    plt.title(col)
    plt.show()
```

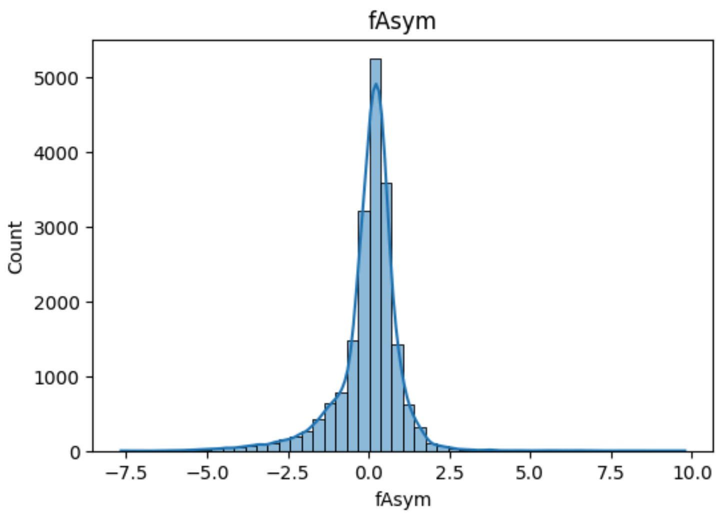

fLength
Count
fLength
0
500
1000
1500
2000
2500
3000
3500
−1
0
1
2
3
4
5
6
7

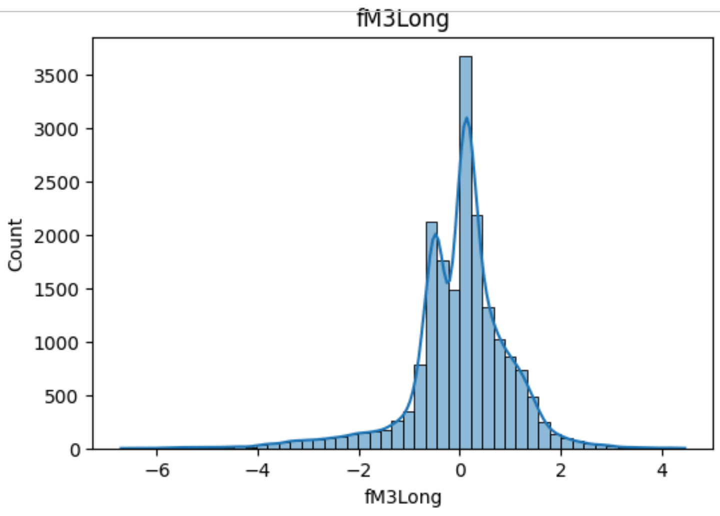

fWidth
Count
fWidth
0
1000
2000
3000
4000
5000
0
2
4
6
8
10
12

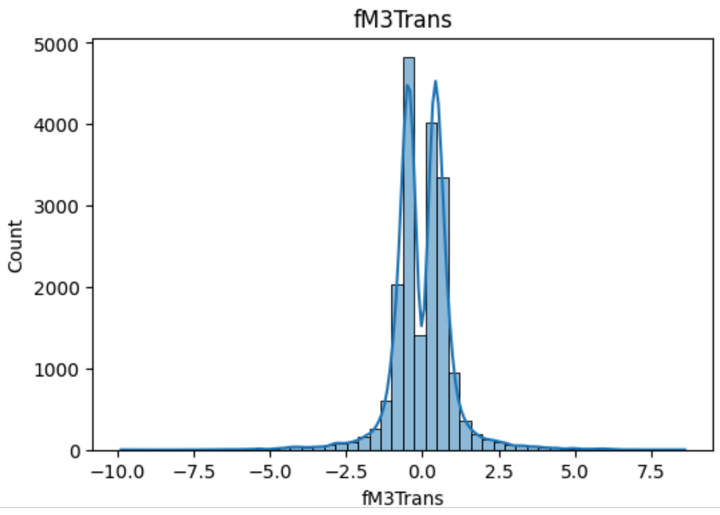

fSize
Count
fSize
0
200
400
600
800
1000
1200
−2
−1
0
1
2
3
4
5


fConc
Count
fConc
0
100
200
300
400
500
600
700
800
−2
−1
0
1
2
3


fConc1
Count
fConc1

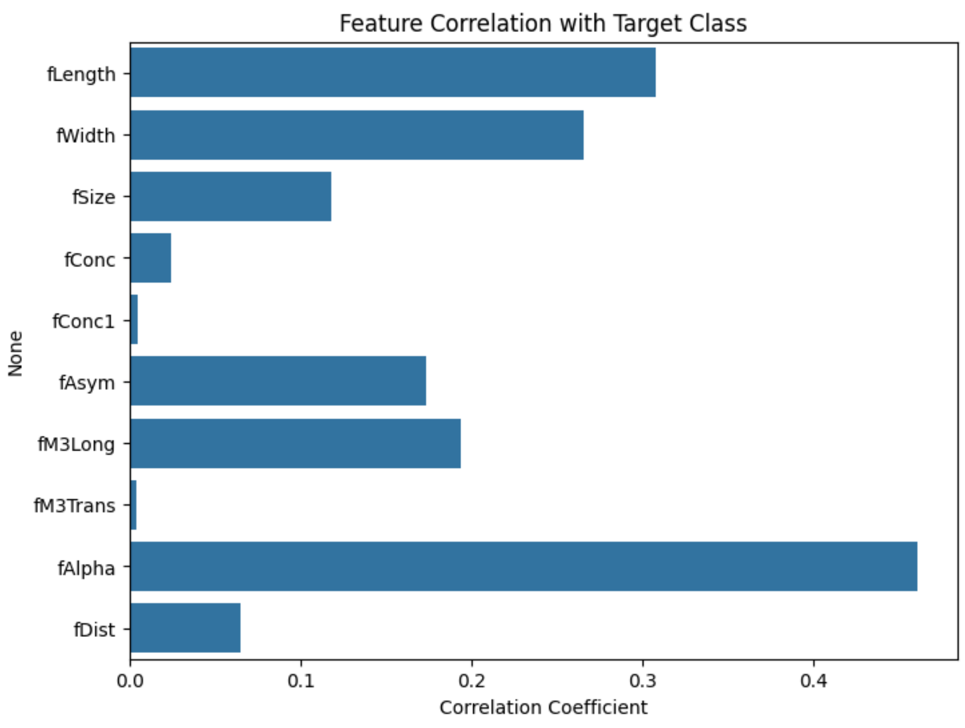

fAsym
Count
fAsym


fM3Long
Count
fM3Long


fM3Trans
Count
fM3Trans

finding correlation between features and target values

```
corr = mgdf.corr(numeric_only=True)["class"].abs()
corr = corr.drop("class")

plt.figure(figsize=(8, 6))
sns.barplot(x=corr.values, y=corr.index)
plt.title("Feature Correlation with Target Class")
plt.xlabel("Correlation Coefficient")
plt.show()
```



selecting features which have higher correlation that `>=0.02`

```
selected_features = corr[corr >= 0.02].index.tolist()

print(f"Using {len(selected_features)} features:")
print(selected_features)

X = X[selected_features]
mgdf = mgdf[selected_features + ["class"]]
```

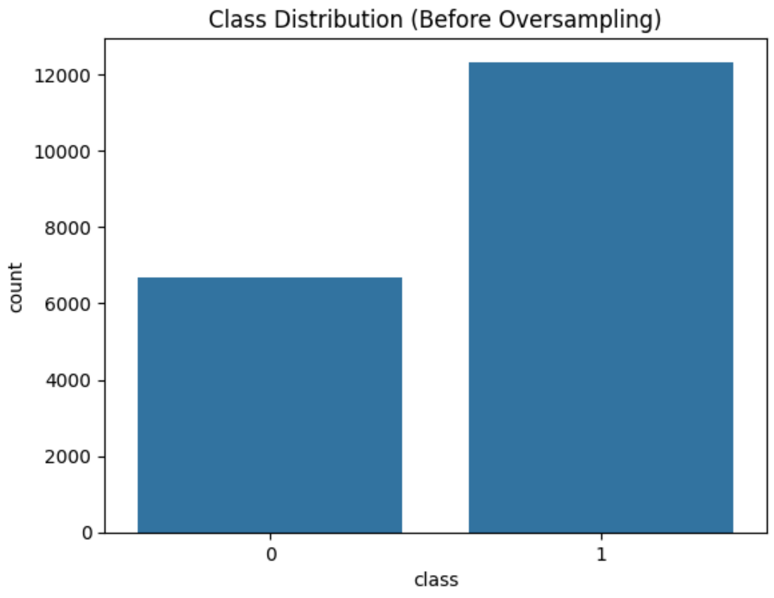
```
Using 8 features:
['fLength', 'fWidth', 'fSize', 'fConc', 'fAsym', 'fM3Long', 'fAlpha', 'fDist']
```

```
top_features = corr[selected_features].sort_values(ascending=False).head(4).index

for tf in top_features:
    sns.boxplot(x=y["class"], y=X[tf])
    plt.title(f"{tf} vs Target Class")
    plt.show()
```

showing class distribution in original data

```
print(y.value_counts())

sns.countplot(x=y["class"])
plt.title("Class Distribution (Before Oversampling)")
plt.show()
```

```
class
1    12332
0     6688
Name: count, dtype: int64
```



Random oversampling data

```
ros = RandomOverSampler(random_state=42)
X_resampled, y_resampled = ros.fit_resample(X, y["class"])
```

```
print(pd.Series(y_resampled).value_counts())

sns.countplot(x=y_resampled)
plt.title("Class Distribution (After Random Oversampling)")
plt.show()
```