Aim - Use SMOTE technique to generate synthetic data.(to solve the problem of class imbalance)

Theory -

Class imbalance occurs when one or more classes have significantly fewer samples than others, which can bias the model's learning process. Various techniques like SMOTE, SMOTEN, SMOTENC, ADASYN, and Safer SMOTE address this issue by generating synthetic samples for the minority classes.

---

1. Basic SMOTE (Synthetic Minority Over-sampling Technique)

- **Purpose:** Balances the class distribution by generating synthetic samples for the minority class using interpolation between existing minority samples.
- **How it Works:**
  - Identifies nearest neighbors for each minority sample.
  - Creates synthetic samples along the line between a minority sample and its neighbors.
- **Limitation:** Not suitable for categorical data directly.

---

2. SMOTEN (SMOTE for Nominal Data)

- **Purpose:** Extends SMOTE to handle categorical data effectively.
- **How it Works:**
  - Uses k-nearest neighbors to generate synthetic samples by selecting and duplicating the category labels of nearest minority samples.
- **Advantage:** Maintains the categorical nature of data without converting it to numerical form.

---

3. SMOTENC (SMOTE for Mixed Data)

- **Purpose:** Designed for datasets with both categorical and numerical features.
- **How it Works:**
  - Treats categorical features differently by copying category values directly.
  - Applies interpolation only on numerical features while ensuring categorical values remain valid.
- **Advantage:** Suitable for real-world datasets with mixed data types.

---

4. ADASYN (Adaptive Synthetic Sampling)

- **Purpose:** Focuses more on samples that are harder to classify (minority samples near the decision boundary).

- **How it Works:**
    - Identifies minority samples that are difficult to learn based on the distribution of nearest neighbors.
    - Generates more synthetic samples for these challenging areas.
- **Advantage:** Reduces the bias towards majority classes by adaptively selecting minority samples.

---

5. Safer SMOTE (SVMSMOTE)

- **Purpose:** Enhances SMOTE by ensuring that synthetic samples do not cross decision boundaries.
- **How it Works:**
    - Utilizes an SVM (Support Vector Machine) to identify safe regions for generating synthetic samples.
    - Prevents the generation of samples in noisy or overlapping regions between classes.
- **Advantage:** Minimizes the risk of creating misleading samples, thus enhancing classifier performance.

Comparison of Techniques

- **Basic SMOTE:** Effective for purely numerical data.
- **SMOTEN:** Suitable for categorical data without numerical features.
- **SMOTENC:** Ideal for mixed datasets (both numerical and categorical features).
- **ADASYN:** Focuses on difficult-to-learn samples, reducing class imbalance near decision boundaries.
- **Safer SMOTE:** Prevents synthetic samples from overlapping into majority class regions, maintaining decision boundaries.

Implementation -

```
#Install Required Libraries
!pip install imbalanced-learn pandas
#Install Required Libraries
import pandas as pd
from imblearn.over_sampling import SMOTE,
SMOTEN, SMOTENC
from sklearn.model_selection import
train_test_split
```

```
#Load the Data
file_path =
'/content/Cleaned_Accumulative_distribution.csv'
data = pd.read_csv(file_path)
# Display basic info
print(data.head())
print("\nClass Distribution Before SMOTE:")
print(data['Type'].value_counts())
```

```
         ID           Type  Movie_number  Fly_number  Other_number  \
0 -1.731908  Dmelanogaster      -1.540178   -1.474087     -1.647509
1 -1.731623  Dmelanogaster      -1.540178   -1.300665     -1.647509
2 -1.731339  Dmelanogaster      -1.540178   -1.127243     -1.647509
3 -1.731054  Dmelanogaster      -1.540178   -0.953821     -1.647509
4 -1.730769  Dmelanogaster      -1.540178   -0.780399     -1.647509
```

```
   Difference_x  Difference_y  Distance
0     -0.291126      0.136903 -0.968219
1     -0.714968     -0.445300 -0.413533
2     -1.780003      1.731326  1.374617
3     -1.871965     -1.020045  0.942211
4     -0.289079      0.247088 -0.897781

Class Distribution Before SMOTE:
Type
Dmelanogaster      4560
Calocasiae(IR)     4180
Calocasiae         3420
Name: count, dtype: int64
```

#Separate Data for SMOTE - features(X) and target(y). Encode Categorical Data

```
from sklearn.preprocessing import LabelEncoder
# Encode the target variable
le = LabelEncoder()
data['Type'] = le.fit_transform(data['Type'])
X = data.drop(columns=['Type', 'ID'])
y = data['Type']
```

#BASIC Smote

```
smote = SMOTE(random_state=42)
X_res, y_res = smote.fit_resample(X, y)
print("\nClass Distribution After Basic SMOTE:")
print(pd.Series(y_res).value_counts())
```

```
Class Distribution After Basic SMOTE:
Type
2    4560
0    4560
1    4560
Name: count, dtype: int64
```

#SMOTEN (For Categorical Data)

```
smoten = SMOTEN(random_state=42)
X_res_n, y_res_n = smoten.fit_resample(X, y)
print("\nClass Distribution After SMOTEN:")
print(pd.Series(y_res_n).value_counts())
```

```
Class Distribution After SMOTEN:
Type
2    4560
0    4560
1    4560
Name: count, dtype: int64
```

#SMOTENC (for Mixed Data: Numeric + Categorical)

```
from numpy import where
# Define categorical feature indices (update as needed)
categorical_features = [X.columns.get_loc('Fly_number')]
smotenc = SMOTENC(categorical_features=categorical_features, random_state=42)
X_res_nc, y_res_nc = smotenc.fit_resample(X, y)
print("\nClass Distribution After SMOTENC:")
print(pd.Series(y_res_nc).value_counts())
```

```
Class Distribution After SMOTENC:
Type
2    4560
0    4560
1    4560
Name: count, dtype: int64
```

#Adaptive SMOTE (ADASYN)

```
from imblearn.over_sampling import ADASYN
adasyn = ADASYN(sampling_strategy={0: 4560}, random_state=42)  # Balance Class 0 to 4560
X_res_ada, y_res_ada = adasyn.fit_resample(X, y)
print("\nClass Distribution After ADASYN:")
print(Counter(y_res_ada))
```

```
Class Distribution After ADASYN:
Counter({0: 4720, 2: 4560, 1: 4180})
```

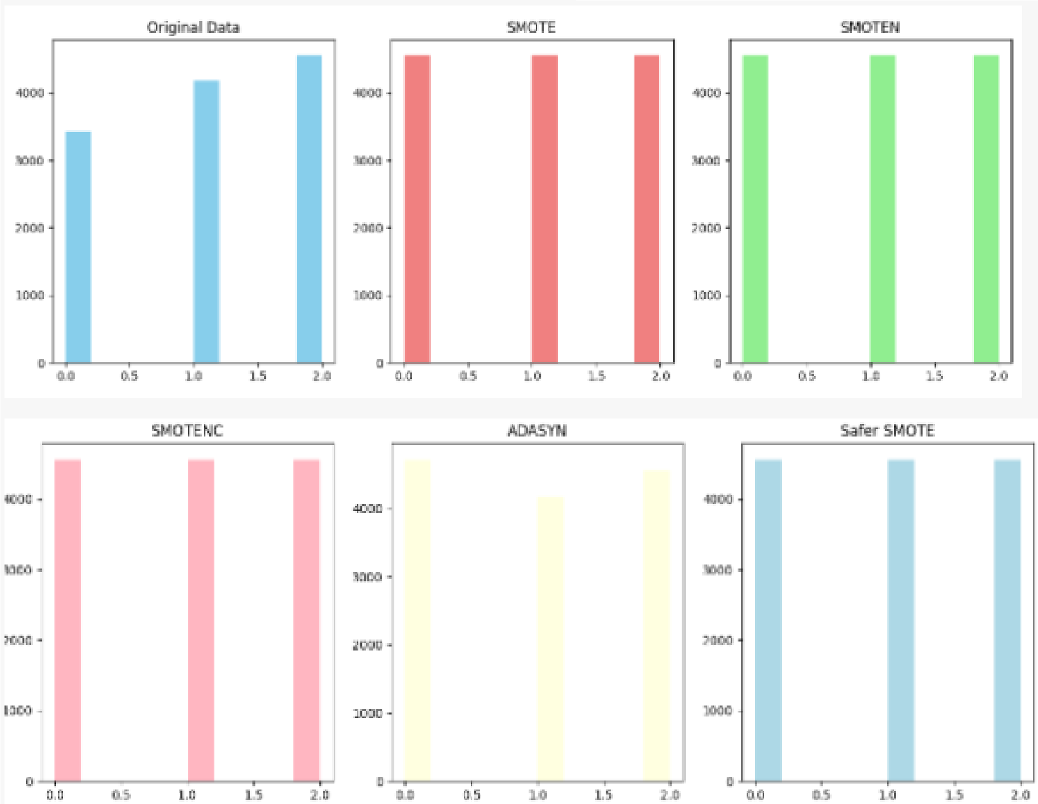
#SAFER SMOTE

```
from imblearn.over_sampling import SVMSMOTE
safer_smote = SVMSMOTE(random_state=42)
X_res_safe, y_res_safe = safer_smote.fit_resample(X, y)
```

```
print("\nClass Distribution After Safer SMOTE:")
print(pd.Series(y_res_safe).value_counts())
```

```
Class Distribution After Safer SMOTE:
Type
2    4560
0    4560
1    4560
Name: count, dtype: int64
```

```
#Comparison Plot for Each Technique
import matplotlib.pyplot as plt
fig, ax = plt.subplots(1, 6, figsize=(30, 5))
ax[0].hist(y, color='skyblue')
ax[0].set_title('Original Data')
ax[1].hist(y_res, color='lightcoral')
ax[1].set_title('SMOTE')
ax[2].hist(y_res_n, color='lightgreen')
ax[2].set_title('SMOTEN')
ax[3].hist(y_res_nc, color='lightpink')
ax[3].set_title('SMOTENC')
ax[4].hist(y_res_ada, color='lightyellow')
ax[4].set_title('ADASYN')
ax[5].hist(y_res_safe, color='lightblue')
ax[5].set_title('Safer SMOTE')
plt.show()
```



Conclusion -

Each technique addresses different aspects of class imbalance:

- **SMOTEN and SMOTENC** handle categorical data efficiently.
- **ADASYN** focuses on hard-to-classify samples to enhance model performance.
- **Safer SMOTE** maintains clean decision boundaries for better classification.