```
1 !pip install pandas
2 !pip install numpy
3
```

```
Requirement already satisfied: pandas in /usr/local/lib/python3.1
Requirement already satisfied: numpy>=1.23.2 in /usr/local/lib/py
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/loc
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/pyt
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/p
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3
Requirement already satisfied: numpy in /usr/local/lib/python3.11
```

```
1 import pandas as pd
2 import numpy as np
```

```
1 from google.colab import drive
2 drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
1 ds_path = f"/content/drive/MyDrive/Intellipaat-sem2/ML Algo/Assign
```

```
1 df_mushroom = pd.read_csv(ds_path)
```

1. Data Exploration

```
1 # 1. The first few rows of the dataset
2 print("df_mushroom.head()")
3 print(df_mushroom.head())
```

```
df_mushroom.head()
  class cap-shape cap-surface cap-color bruises odor gill-attachm
0     p         x           s         n       t    p
1     e         x           s         y       t    a
2     e         b           s         w       t    l
3     p         x           y         w       t    p
4     e         x           s         g       f    n

  gill-spacing gill-size gill-color  ... stalk-surface-below-ring
0            c         n          k  ...                        s
1            c         b          k  ...                        s
2            c         b          n  ...                        s
3            c         n          n  ...                        s
4            w         b          k  ...                        s

  stalk-color-above-ring stalk-color-below-ring veil-type veil-co
0                      w                      w         p
1                      w                      w         p
2                      w                      w         p
3                      w                      w         p
4                      w                      w         p

  ring-number ring-type spore-print-color population habitat
0           o         p                 k          s       u
1           o         p                 n          n       g
2           o         p                 n          n       m
3           o         p                 k          s       u
4           o         e                 n          a       g

[5 rows x 23 columns]
```

```
1
2 # 2. Info of dataset (column names, non-null count, data types)
```

Resources

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You currently have zero compute units available. Resources offered free of charge are not guaranteed. Purchase more units here.

At your current usage level, this runtime may last up to 2 hours 30 minutes.

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Want more memory and disk space?

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Python 3 Google Compute Engine backend (GPU)

Showing resources from 8:09 AM to 9:25 AM

System RAM
2.1 / 12.7 GB

GPU RAM
0.0 / 15.0 GB

Disk
31.1 / 112.6 GB

```
print("Dataset Info:")
print(df_mushroom.info())
```

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8124 entries, 0 to 8123
Data columns (total 23 columns):
 #   Column                    Non-Null Count  Dtype 
---  ------                    --------------  ----- 
 0   class                     8124 non-null   object
 1   cap-shape                 8124 non-null   object
 2   cap-surface               8124 non-null   object
 3   cap-color                 8124 non-null   object
 4   bruises                   8124 non-null   object
 5   odor                      8124 non-null   object
 6   gill-attachment           8124 non-null   object
 7   gill-spacing              8124 non-null   object
 8   gill-size                 8124 non-null   object
 9   gill-color                8124 non-null   object
 10  stalk-shape               8124 non-null   object
 11  stalk-root                8124 non-null   object
 12  stalk-surface-above-ring  8124 non-null   object
 13  stalk-surface-below-ring  8124 non-null   object
 14  stalk-color-above-ring    8124 non-null   object
 15  stalk-color-below-ring    8124 non-null   object
 16  veil-type                 8124 non-null   object
 17  veil-color                8124 non-null   object
 18  ring-number               8124 non-null   object
 19  ring-type                 8124 non-null   object
 20  spore-print-color         8124 non-null   object
 21  population                8124 non-null   object
 22  habitat                   8124 non-null   object
dtypes: object(23)
memory usage: 1.4+ MB
None
```

```
# 3. Look for missing values
print("\nMissing Values in Each Column:")
print(df_mushroom.isnull().sum())

# Get the columns with missing values
columns_with_nulls = df_mushroom.columns[df_mushroom.isnull().any()]

# Print the column names with missing values
print("Columns with missing values:")
print(columns_with_nulls)
```

```

Missing Values in Each Column:
class                       0
cap-shape                   0
cap-surface                 0
cap-color                   0
bruises                     0
odor                        0
gill-attachment             0
gill-spacing                0
gill-size                   0
gill-color                  0
stalk-shape                 0
stalk-root                  0
stalk-surface-above-ring    0
stalk-surface-below-ring    0
stalk-color-above-ring      0
stalk-color-below-ring      0
veil-type                   0
veil-color                  0
ring-number                 0
ring-type                   0
spore-print-color           0
population                  0
habitat                     0
dtype: int64
```

```
Columns with missing values:
Index([], dtype='object')
```

```
# 4. unique values in each column
print("\nUnique Values in Each Column:")
for column in df_mushroom.columns:
    print(f"{column}: {df_mushroom[column].nunique()} unique values")
```

```
Unique Values in Each Column:
class: 2 unique values
cap-shape: 6 unique values
cap-surface: 4 unique values
cap-color: 10 unique values
bruises: 2 unique values
odor: 9 unique values
gill-attachment: 2 unique values
gill-spacing: 2 unique values
gill-size: 2 unique values
gill-color: 12 unique values
stalk-shape: 2 unique values
stalk-root: 5 unique values
stalk-surface-above-ring: 4 unique values
stalk-surface-below-ring: 4 unique values
stalk-color-above-ring: 9 unique values
stalk-color-below-ring: 9 unique values
veil-type: 1 unique values
veil-color: 4 unique values
ring-number: 3 unique values
ring-type: 5 unique values
spore-print-color: 9 unique values
population: 6 unique values
habitat: 7 unique values
```

```
# 5. Distribution of the target variable ('class')
print("\nTarget Variable [ class ] Distribution:")
print(df_mushroom['class'].value_counts())
```

```
Target Variable [ class ] Distribution:
class
e    4208
p    3916
Name: count, dtype: int64
```

```
# 6. Basic statistics
print("\nBasic Statistics:")
print(df_mushroom.describe(include='all'))
```

```
Basic Statistics:
       class cap-shape cap-surface cap-color bruises  odor gill-a
count   8124      8124        8124      8124    8124  8124
unique     2         6           4        10       2     9
top        e         x           y         n       f     n
freq    4208      3656        3244      2284    4748  3528

       gill-spacing gill-size gill-color  ... stalk-surface-below
count          8124      8124       8124  ...
unique            2         2         12  ...
top               c         b          b  ...
freq           6812      5612       1728  ...

       stalk-color-above-ring stalk-color-below-ring veil-type ve
count                    8124                   8124      8124
unique                      9                      9         1
top                         w                      w         p
freq                     4464                   4384      8124

       ring-number ring-type spore-print-color population habitat
count         8124      8124              8124       8124    8124
unique           3         5                 9          6       7
```

```
top              o         p                w          v       d
freq          7488      3968             2388       4040    3148

[4 rows x 23 columns]
```

```
# 7. Check the distribution of values for each categorical column
for column in df_mushroom.columns:
    print(f"\nValue Counts for {column}:")
    print(df_mushroom[column].value_counts())
```

```
stalk-color-below-ring
w    4384
p    1872
g     576
n     512
b     432
o     192
e      96
c      36
y      24
Name: count, dtype: int64

Value Counts for veil-type:
veil-type
p    8124
Name: count, dtype: int64

Value Counts for veil-color:
veil-color
w    7924
n      96
o      96
y       8
Name: count, dtype: int64

Value Counts for ring-number:
ring-number
o    7488
t     600
n      36
Name: count, dtype: int64

Value Counts for ring-type:
ring-type
p    3968
e    2776
l    1296
f      48
n      36
Name: count, dtype: int64

Value Counts for spore-print-color:
spore-print-color
w    2388
n    1968
k    1872
h    1632
r      72
u      48
o      48
y      48
b      48
Name: count, dtype: int64

Value Counts for population:
population
v    4040
y    1712
s    1248
```

```
print(df_mushroom.shape)
```

```
(8124, 23)
```

```
# Remove data with any missing information for now
null_columns = len(columns_with_nulls)
print(null_columns)
if (null_columns > 0):
  df_mushroom = df_mushroom.dropna()
```

```
0
```

```
print(df_mushroom.shape)
```

```
(8124, 23)
```

```
# Get summary stats for the categorical features
df_mushroom.describe(include = ['O'])
```

	class	cap-shape	cap-surface	cap-color	bruises	odor	gill-attachment	s
count	8124	8124	8124	8124	8124	8124	8124	
unique	2	6	4	10	2	9	2	
top	e	x	y	n	f	n	f	
freq	4208	3656	3244	2284	4748	3528	7914	

4 rows × 23 columns

```
df_mushroom.describe()
```

	class	cap-shape	cap-surface	cap-color	bruises	odor	gill-attachment	s
count	8124	8124	8124	8124	8124	8124	8124	
unique	2	6	4	10	2	9	2	
top	e	x	y	n	f	n	f	
freq	4208	3656	3244	2284	4748	3528	7914	

4 rows × 23 columns

```
# Create the feature/flag for eatable / non eatable
df_mushroom['class'] = df_mushroom['class'].apply(lambda x: 1 if x
```

```
df_mushroom.head()
```

	class	cap-shape	cap-surface	cap-color	bruises	odor	gill-attachment	gill spacir
0	0	x	s	n	t	p	f	
1	1	x	s	y	t	a	f	
2	1	b	s	w	t	l	f	
3	0	x	y	w	t	p	f	
4	1	x	s	g	f	n	f	

5 rows × 23 columns

```
1 # Check the event rate
2 df_mushroom['class'].value_counts()/len(df_mushroom)
```

class	count
1	0.517971
0	0.482029

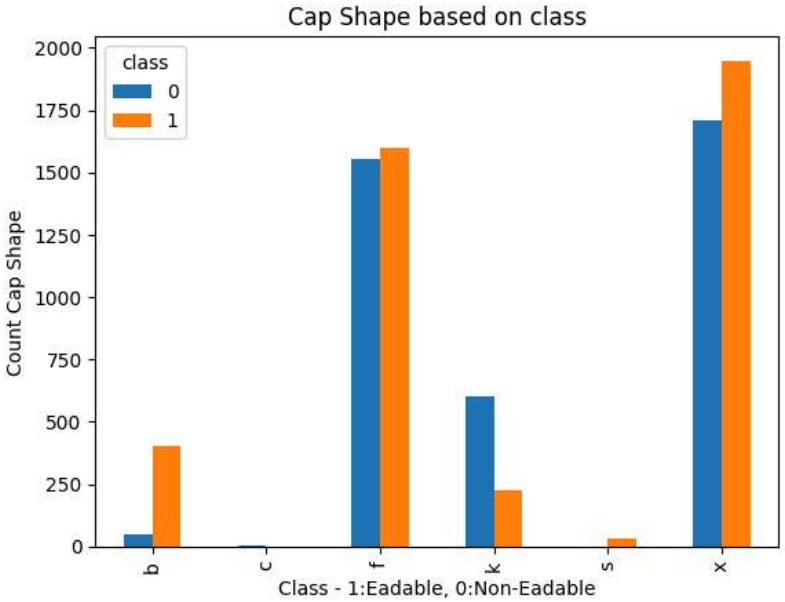
dtype: float64

```
1 !pip install matplotlib
2 !pip install seaborn
```

```
Requirement already satisfied: matplotlib in /usr/local/lib/pytho
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/pyt
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/li
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/li
Requirement already satisfied: numpy>=1.23 in /usr/local/lib/pyth
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/
Requirement already satisfied: pillow>=8 in /usr/local/lib/python
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib
Requirement already satisfied: python-dateutil>=2.7 in /usr/local
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3
Requirement already satisfied: seaborn in /usr/local/lib/python3.
Requirement already satisfied: numpy!=1.24.0,>=1.20 in /usr/local
Requirement already satisfied: pandas>=1.2 in /usr/local/lib/pyth
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in /usr/lo
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/pyt
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/li
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/li
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/
Requirement already satisfied: pillow>=8 in /usr/local/lib/python
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib
Requirement already satisfied: python-dateutil>=2.7 in /usr/local
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/pyt
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/p
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3
```

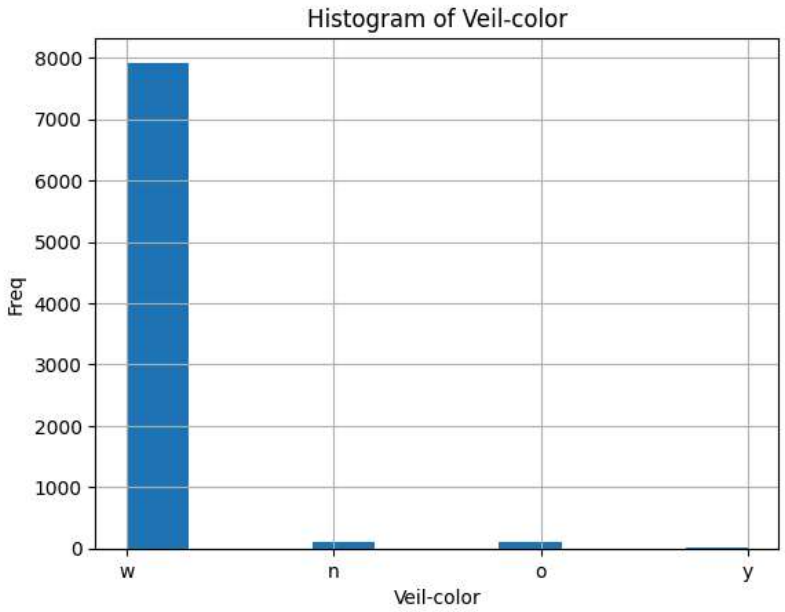
```
1 import matplotlib.pyplot as plt
2 import seaborn as sns
3
4 pd.crosstab(df_mushroom['cap-shape'],df_mushroom['class']).plot(kind
5 plt.title('Cap Shape based on class')
6 plt.xlabel('Class - 1:Eadable, 0:Non-Eadable')
7 plt.ylabel('Count Cap Shape')
```

```
Text(0, 0.5, 'Count Cap Shape')
```




```
#veil-color: brown=n,orange=o,white=w,yellow=y

df_mushroom['veil-color'].hist()
plt.title('Histogram of Veil-color')
plt.xlabel('Veil-color')
plt.ylabel('Freq')

```

```
Text(0, 0.5, 'Freq')
```




```
# Convert the categorical features
# Creating dummies for all these variables
d_cap_shape = pd.get_dummies(df_mushroom['cap-shape'], prefix='cap
d_cap_surface = pd.get_dummies(df_mushroom['cap-surface'], prefix=
d_cap_color = pd.get_dummies(df_mushroom['cap-color'], prefix='cap
d_bruises = pd.get_dummies(df_mushroom['bruises'], prefix='bruises
d_odor = pd.get_dummies(df_mushroom['odor'], prefix='odor',dtype=i
d_gill_attachment = pd.get_dummies(df_mushroom['gill-attachment'],
```

```
d_gill_spacing = pd.get_dummies(df_mushroom['gill-spacing'], prefi
d_gill_size = pd.get_dummies(df_mushroom['gill-size'], prefix='gil
d_gill_color = pd.get_dummies(df_mushroom['gill-color'], prefix='g
d_stalk_shape = pd.get_dummies(df_mushroom['stalk-shape'], prefix=
d_stalk_root = pd.get_dummies(df_mushroom['stalk-root'], prefix='s
d_stalk_surface_above_ring = pd.get_dummies(df_mushroom['stalk-sur
d_stalk_surface_below_ring = pd.get_dummies(df_mushroom['stalk-sur
d_stalk_color_above_ring = pd.get_dummies(df_mushroom['stalk-color
d_stalk_color_below_ring = pd.get_dummies(df_mushroom['stalk-color
d_veil_type = pd.get_dummies(df_mushroom['veil-type'], prefix='vei
d_veil_color = pd.get_dummies(df_mushroom['veil-color'], prefix='v
d_ring_number = pd.get_dummies(df_mushroom['ring-number'], prefix=
d_ring_type = pd.get_dummies(df_mushroom['ring-type'], prefix='rin
d_spore_print_color = pd.get_dummies(df_mushroom['spore-print-colo
d_population = pd.get_dummies(df_mushroom['population'], prefix='p
d_habitat = pd.get_dummies(df_mushroom['habitat'], prefix='habitat


```

```
# Create the final dataset with all the relevant features - both d
feature_x_cont = ['class','cap-shape','cap-surface','cap-color','b

df_mushroom_cont = df_mushroom[feature_x_cont]

# Creating the Final data with all the relevant fields and Dep Var
df_mushroom_new = pd.concat([df_mushroom['class'],d_cap_shape,d_ca
```

```
df_mushroom_new.shape
```

```
(8124, 118)
```

```
df_mushroom_new.head()
```

	class	cap-shape_b	cap-shape_c	cap-shape_f	cap-shape_k	cap-shape_s	cap-shape_x	su
0	0	0	0	0	0	0	1	
1	1	0	0	0	0	0	1	
2	1	1	0	0	0	0	0	
3	0	0	0	0	0	0	1	
4	1	0	0	0	0	0	1	

5 rows × 118 columns

```
df_mushroom_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8124 entries, 0 to 8123
Columns: 118 entries, class to habitat_w
dtypes: int64(118)
memory usage: 7.3 MB
```

Train Test Split

Double-click (or enter) to edit

```
#X = df_mushroom_new.drop('class', axis=1)
#y = df_mushroom_new['class']

```

```
X = df_mushroom.drop('class', axis=1)
y = df_mushroom['class']

X = X.map(lambda x: ord(x))
```

```
from sklearn.model_selection import train_test_split
```

```
X_train,X_test,y_train,y_test=train_test_split(X,y,train_size=0.75
```

Model Building

```
import sklearn.metrics as metrics
from sklearn.linear_model import LogisticRegression
```

```
from sklearn.datasets import make_classification
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.metrics import accuracy_score
```

```
# Step 3: Define the model
model = RandomForestClassifier(random_state=42)

# Step 4: Define the hyperparameter grid
param_grid = {
    'n_estimators': [50, 100, 150],        # Number of trees in th
    'max_depth': [None, 10, 20],           # Maximum depth of the
    'min_samples_split': [2, 5, 10],       # Minimum number of sam
    'min_samples_leaf': [1, 2, 4]          # Minimum number of sam
}

# Step 5: Set up GridSearchCV
grid_search = GridSearchCV(
    estimator=model,
    param_grid=param_grid,
    cv=5,                  # 5-fold cross-validation
    scoring='accuracy',    # Performance metric
    verbose=1,             # Print progress
    n_jobs=-1              # Use all available CPU cores
)

# Step 6: Perform the grid search
grid_search.fit(X_train, y_train)

# Step 7: Print the best hyperparameters and score
print("Best Parameters:", grid_search.best_params_)
print("Best Cross-Validation Accuracy:", grid_search.best_score_)

# Step 8: Evaluate the model on the test set
best_model = grid_search.best_estimator_
y_pred = best_model.predict(X_test)
test_accuracy = accuracy_score(y_test, y_pred)
print("Test Set Accuracy:", test_accuracy)
```

```
Fitting 5 folds for each of 81 candidates, totalling 405 fits
Best Parameters: {'max_depth': None, 'min_samples_leaf': 1, 'min_
Best Cross-Validation Accuracy: 1.0
Test Set Accuracy: 1.0
```

```
best_model.fit(X_train, y_train)
```

```
RandomForestClassifier
RandomForestClassifier(n_estimators=50, random_state=42)
```

```
1 best_model.score(X_train,y_train)
```

```
1.0
```

Model Prediction

```
1 y_train_pred=best_model.predict(X_train)
```

```
1 y_test_pred=best_model.predict(X_test)
```

Model Evaluation

```
1 from sklearn.metrics import confusion_matrix,accuracy_score,recall_
```

```
1 print('Train Accuracy:',accuracy_score(y_train,y_train_pred))
2 print('Test Accuracy:',accuracy_score(y_test,y_test_pred))
3 print('Train Recall:',recall_score(y_train,y_train_pred))
4 print('Test Recall:',recall_score(y_test,y_test_pred))
5 print('Train Precision:',precision_score(y_train,y_train_pred))
6 print('Test Precision:',precision_score(y_test,y_test_pred))
7 print('Train F1 Score:',f1_score(y_train,y_train_pred))
8 print('Test F1 Score:',f1_score(y_test,y_test_pred))
```

```
Train Accuracy: 1.0
Test Accuracy: 1.0
Train Recall: 1.0
Test Recall: 1.0
Train Precision: 1.0
Test Precision: 1.0
Train F1 Score: 1.0
Test F1 Score: 1.0
```

```
1 print(classification_report(y_train,y_train_pred))
2 print("xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
3 print(classification_report(y_test,y_test_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2925
           1       1.00      1.00      1.00      3168

    accuracy                           1.00      6093
   macro avg       1.00      1.00      1.00      6093
weighted avg       1.00      1.00      1.00      6093

xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       991
           1       1.00      1.00      1.00      1040

    accuracy                           1.00      2031
   macro avg       1.00      1.00      1.00      2031
weighted avg       1.00      1.00      1.00      2031
```

```
from sklearn.tree import DecisionTreeClassifier
```

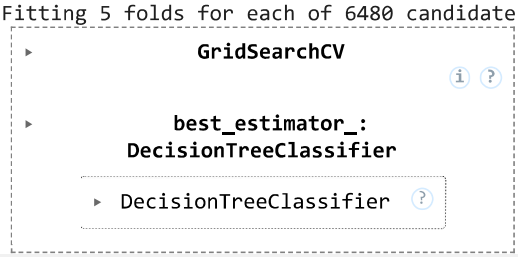
```
DT_gcv=DecisionTreeClassifier()
```

```
param_grid = {'max_features': ['sqrt', 'log2'],
              'ccp_alpha': [1,0.1, .01, .001,0.0001,0.00001],
              'max_depth' : [4,5,6,7,8,9,10,11,12,15],
              'criterion' :['gini', 'entropy','log_loss'],
              'splitter' :['best', 'random'],
              'min_samples_split': [2, 5, 10],
              'min_samples_leaf': [1, 2, 4]
             }
```

```
model_cv=GridSearchCV(DT_gcv,param_grid,scoring="f1",verbose=2,cv=
```

```
model_cv.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 6480 candidates, totalling 32400 fits
```




```
best_model=model_cv.best_estimator_
best_param=model_cv.best_params_
```

```
print(best_param)
```

```
{'ccp_alpha': 0.001, 'criterion': 'entropy', 'max_depth': 10, 'ma
```

```
best_model.fit(X_train,y_train)
```

```
y_train_pred_cv=best_model.predict(X_train)
```

```
y_test_pred_cv=best_model.predict(X_test)
```

```
print(classification_report(y_train,y_train_pred_cv))
print("XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX")
print(classification_report(y_test,y_test_pred_cv))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2925
           1       1.00      1.00      1.00      3168

    accuracy                           1.00      6093
   macro avg       1.00      1.00      1.00      6093
weighted avg       1.00      1.00      1.00      6093

XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       991
           1       1.00      1.00      1.00      1040

    accuracy                           1.00      2031
   macro avg       1.00      1.00      1.00      2031
weighted avg       1.00      1.00      1.00      2031
```

Linear Regression is a basic supervised machine learning algorithm where the relationship between the dependent variable and one or more independent variables is modeled by a straight line (linear equation).

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV

# Define the model
model = LogisticRegression( )  # Increase max_iter as needed


```

```
model.fit(X_train,y_train)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_log
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver opt
    https://scikit-learn.org/stable/modules/linear_model.html#log
  n_iter_i = _check_optimize_result(
```

▾ LogisticRegression

LogisticRegression()

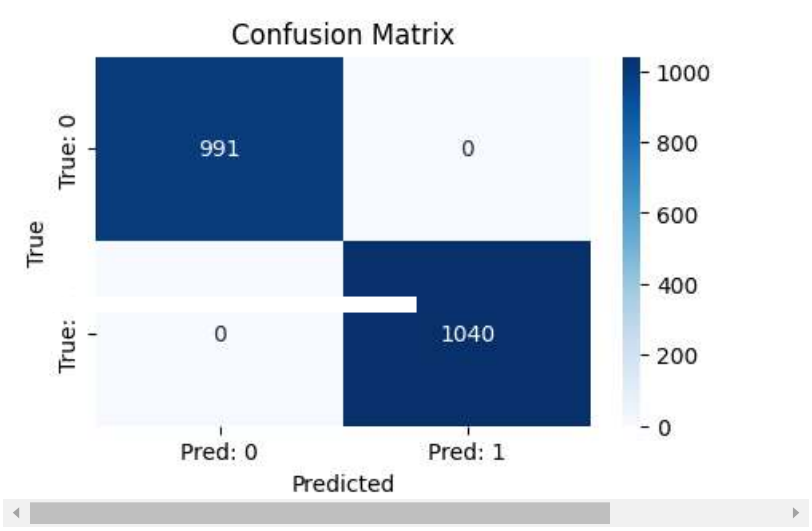
```
y_train_pred = model.predict(X_test)
y_test_pred = model.predict(X_test)


```

```
print('Train Accuracy:',accuracy_score(y_train,y_train_pred))
print('Test Accuracy:',accuracy_score(y_test,y_test_pred))
print('Train Recall:',recall_score(y_train,y_train_pred))
print('Test Recall:',recall_score(y_test,y_test_pred))
print('Train Precision:',precision_score(y_train,y_train_pred))
print('Test Precision:',precision_score(y_test,y_test_pred))
print('Train F1 Score:',f1_score(y_train,y_train_pred))
print('Test F1 Score:',f1_score(y_test,y_test_pred))
print('Train roc_auc_score:',roc_auc_score(y_train,y_train_pred))
print('Test roc_auc_score:',roc_auc_score(y_test,y_test_pred))
```

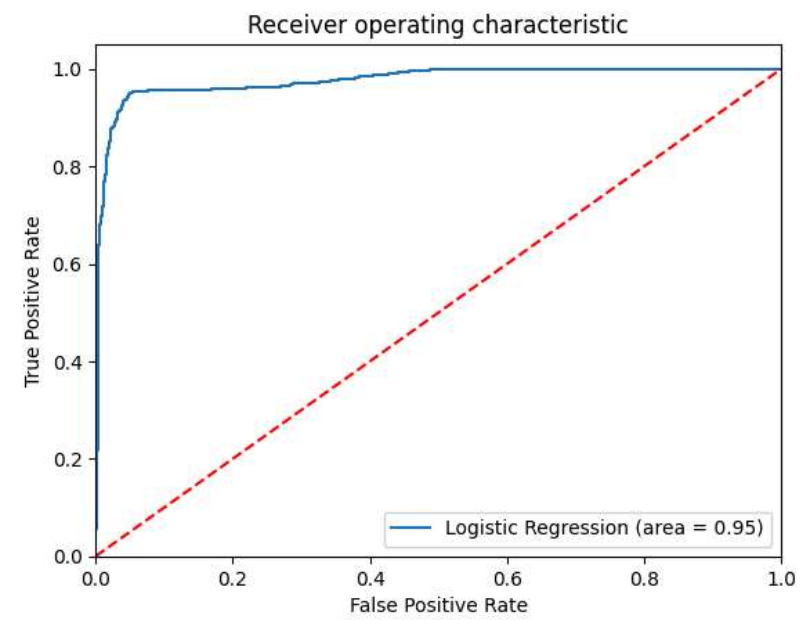
```
Train Accuracy: 1.0
Test Accuracy: 1.0
Train Recall: 1.0
Test Recall: 1.0
Train Precision: 1.0
Test Precision: 1.0
Train F1 Score: 1.0
Test F1 Score: 1.0
Train roc_auc_score: 1.0
Test roc_auc_score: 1.0
```

```
from sklearn.metrics import confusion_matrix

# Generate confusion matrix
cm = confusion_matrix(y_test,y_test_pred)

# Plot confusion matrix as a heatmap
plt.figure(figsize=(5, 3))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['P
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
```

```
plt.ylabel('True')
plt.show()
```




```
# a graph that shows how well a model performs across all possible
# against the false positive rate (FPR)
from sklearn.metrics import roc_curve
logit_roc_auc = roc_auc_score(y_test, model.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, model.predict_proba(X_tes
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % lo
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
plt.show()
```



Hyperparameter tuning with GridSearchCv

```
from sklearn.metrics import classification_report# Define the para
param_grid = {
    'C': [0.01, 0.1, 1, 10, 100],  # Inverse of regularization str
    'solver': ['lbfgs', 'liblinear', 'saga'],  # Solvers
    'l1_ratio': [0, 0.5, 1],  # Used only with elasticnet
}

# Initialize GridSearchCV
grid_search = GridSearchCV(estimator=model,
                           param_grid=param_grid,
                           cv=5,
                           scoring='accuracy',
                           verbose=1,
                           n_jobs=-1)

# Fit the model
grid_search.fit(X_train, y_train)

# Best parameters and model
print("Best Parameters:", grid_search.best_params_)
best_model = grid_search.best_estimator_

# Evaluate the model
y_pred = best_model.predict(X_test)
print("\nClassification Report:\n", classification_report(y_test,
```

```
Fitting 5 folds for each of 45 candidates, totalling 225 fits
Best Parameters: {'C': 10, 'l1_ratio': 0, 'solver': 'liblinear'}

Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       991
           1       1.00      1.00      1.00      1040

    accuracy                           1.00      2031
   macro avg       1.00      1.00      1.00      2031
weighted avg       1.00      1.00      1.00      2031

/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_log
  warnings.warn(
```

```
best_model.fit(X_train,y_train)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_log
  warnings.warn(
```

```
LogisticRegression(C=10, l1_ratio=0, solver='liblinear')
```

```
y_test_tred = model.predict(X_test)
```

SVM

```
from sklearn.svm import SVC
svm = SVC(kernel='rbf',random_state=0,probability=True)
svm.fit(X_train,y_train)
```

```
SVC(probability=True, random_state=0)
```

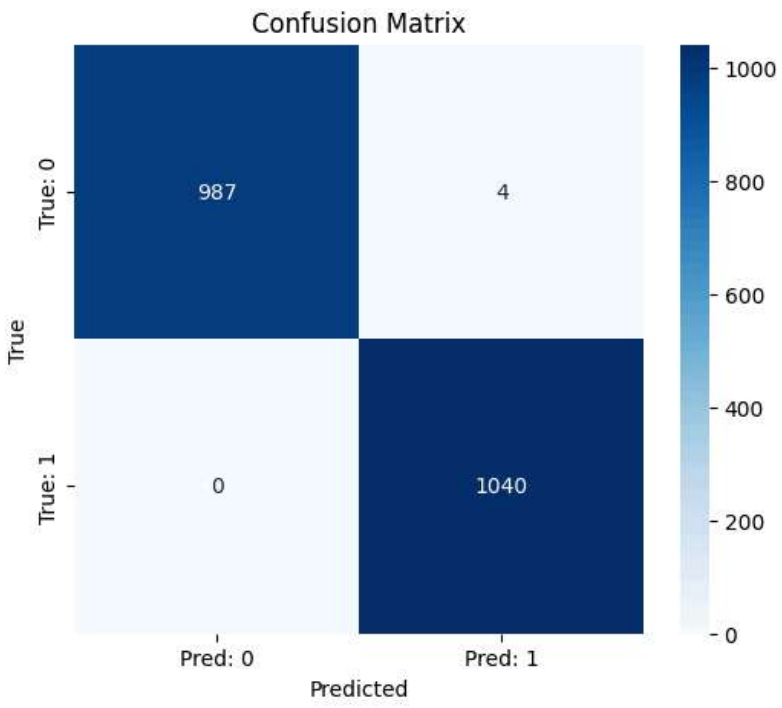
```
y_test_pred = svm.predict(X_test)
```

```
y_train_pred = svm.predict(X_train)
```

```
print('Train Accuracy:',accuracy_score(y_train,y_train_pred))
print('Test Accuracy:',accuracy_score(y_test,y_test_pred))
print('Train Recall:',recall_score(y_train,y_train_pred))
print('Test Recall:',recall_score(y_test,y_test_pred))
print('Train Precision:',precision_score(y_train,y_train_pred))
print('Test Precision:',precision_score(y_test,y_test_pred))
print('Train F1 Score:',f1_score(y_train,y_train_pred))
print('Test F1 Score:',f1_score(y_test,y_test_pred))
print('Train roc_auc_score:',roc_auc_score(y_train,y_train_pred))
print('Test roc_auc_score:',roc_auc_score(y_test,y_test_pred))
```

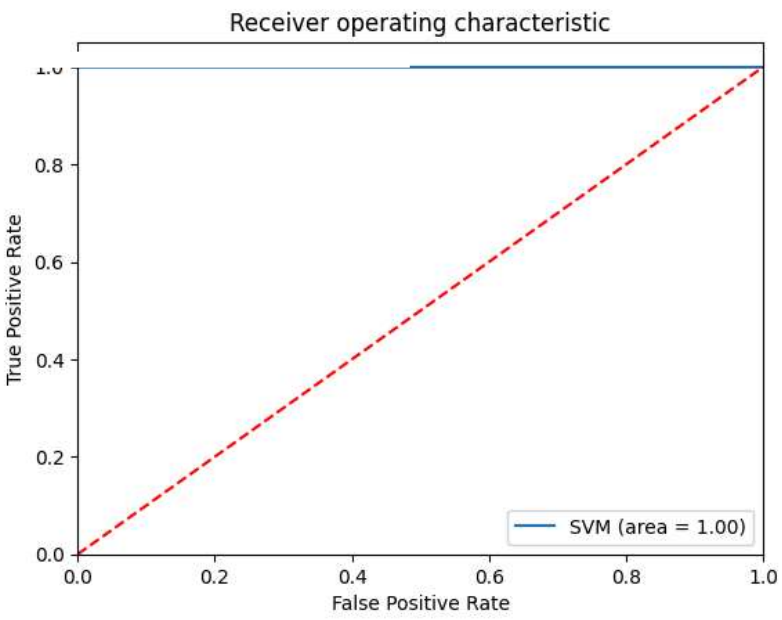
```
Train Accuracy: 0.995240439849007
Test Accuracy: 0.9980305268340719
Train Recall: 0.9996843434343434
Test Recall: 1.0
Train Precision: 0.9912363067292644
Test Precision: 0.9961685823754789
Train F1 Score: 0.9954424013829954
Test F1 Score: 0.9980806142034548
Train roc_auc_score: 0.9950558469308469
Test roc_auc_score: 0.9979818365287588
```

```
from sklearn.metrics import confusion_matrix

# Generate confusion matrix
cm = confusion_matrix(y_test, y_test_pred)

# Plot confusion matrix as a heatmap
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['P
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```




```
# a graph that shows how well a model performs across all possible
# against the false positive rate (FPR)
```

```
from sklearn.metrics import roc_curve
logit_roc_auc = roc_auc_score(y_test, svm.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, svm.predict_proba(X_test)
plt.figure()
plt.plot(fpr, tpr, label='SVM (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
plt.show()
```




```
# Define the parameter grid for GridSearchCV
param_grid = {
    'C': [0.1, 1, 10, 100],  # Regularization parameter
    'kernel': ['linear', 'poly', 'rbf', 'sigmoid'],  # Kernel types
}

# Initialize GridSearchCV
grid_search_svm = GridSearchCV(estimator=svm,
                               param_grid=param_grid,
                               cv=5,
                               scoring='accuracy',
                               verbose=1,
                               n_jobs=-1)

# Fit the model
grid_search_svm.fit(X_train, y_train)

# Best parameters and model
print("Best Parameters:", grid_search_svm.best_params_)
best_model_svm = grid_search_svm.best_estimator_

# Evaluate the model
y_test_pred = best_model_svm.predict(X_test)
print("\nClassification Report:\n", classification_report(y_test, y_

```

```
Fitting 5 folds for each of 16 candidates, totalling 80 fits
```

**Conclusion : Three Models are tried **

1. RandomForestClassifier
2. DecisionTreeClassifier
3. LogisticRegression
4. SVM

Change runtime type