Problem Statement:

Data Set Information: This data set includes descriptions of hypothetical samples corresponding to 23 species of gilled mushrooms in the Agaricus and Lepiota Family (pp. 500-525). Each species is identified as definitely edible, definitely poisonous, or of unknown edibility and not recommended. This latter class was combined with the poisonous one. The Guide clearly states that there is no simple rule for determining the edibility of a mushroom; no rule like ``leaflets three, let it be'' for Poisonous Oak and Ivy.

Importing requried libraries

In [32]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import pickle
import seaborn as sns
from category_encoders import BinaryEncoder
from scipy.stats import zscore
import statsmodels.api as sm
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import power_transform, StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import confusion_matrix, classification_report, accuracy_sc
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

Display Maximum columns and rows

In [2]:

```
pd.set_option("display.max_columns", None)
pd.set_option("display.max_rows",None)
```

Reading Data

In [3]:
```
df = pd.read_csv(r"C:\Users\Kushal Arya\Desktop\Data Analysis With Python\ML File
df.head()
```

Out[3]:

	class	cap-shape	cap-surface	cap-color	bruises	odor	gill-attachment	gill-spacing	gill-size	gill-color	stalk-shape	stalk-root	su
0	p	x	s	n	t	p	f	c	n	k	e	e	
1	e	x	s	y	t	a	f	c	b	k	e	c	
2	e	b	s	w	t	l	f	c	b	n	e	c	
3	p	x	y	w	t	p	f	c	n	n	e	e	
4	e	x	s	g	f	n	f	w	b	k	t	e	

In [4]:
```
# Here we use shape command to know total no of rows and columns present in our d

print('Rows and Columns in Dataset : ', df.shape )
```

```
Rows and Columns in Dataset :  (8124, 23)
```

In [5]:
```python
# Here we use info command to know all details about dataset i.e, size, type etc.
print('-------------------------------------------------------------------------
print('\nInformations of dataset :-\n')
print(df.info())
print('\n-----------------------------------------------------------------------
```

```
---------------------------------------------------------------------------

Informations of dataset :-

<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

---------------------------------------------------------------------------
```

Our dataset set has all object value we need to apply encoding technique.

In [6]:
```python
# Here we use isna() command to identify of nan in our dataset.
print('------------------------------------------------------------------------
print('\nNaN in dataset :-\n')
print(df.isna().sum())
print('\n-----------------------------------------------------------------------
```

```
---------------------------------------------------------------------------

NaN in dataset :-

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

---------------------------------------------------------------------------
```

There is no null values in dataset.

Checking class imbalence

In [7]:
```python
df['class'].value_counts()
```

Out[7]:
```
e    4208
p    3916
Name: class, dtype: int64
```

Dataset is balance.

Label Encoder

In [8]:
```
lab_enc = LabelEncoder()
y = lab_enc.fit_transform(df['class'])
y
```

Out[8]:
```
array([1, 0, 0, ..., 0, 1, 0])
```

Binary Encoder

In [9]:
```
bi_enc = BinaryEncoder()
x = bi_enc.fit_transform(df)
x.head()
```

Out[9]:

	class_0	class_1	cap-shape_0	cap-shape_1	cap-shape_2	cap-shape_3	cap-surface_0	cap-surface_1	cap-surface_2	ca color_
0	0	1	0	0	0	1	0	0	1	
1	1	0	0	0	0	1	0	0	1	
2	1	0	0	0	1	0	0	0	1	
3	0	1	0	0	0	1	0	1	0	
4	1	0	0	0	0	1	0	0	1	

Above we encode our categorical data into binary.

In [10]:
```
# Here we use shape command to know total no of rows and columns present in our d

print('Rows and Columns in Dataset : ', x.shape )
```

```
Rows and Columns in Dataset :  (8124, 78)
```

Drop repeated class

In [11]:
```python
x = x.drop(columns = ['class_0', 'class_1'], axis = 1)
x.head()
```

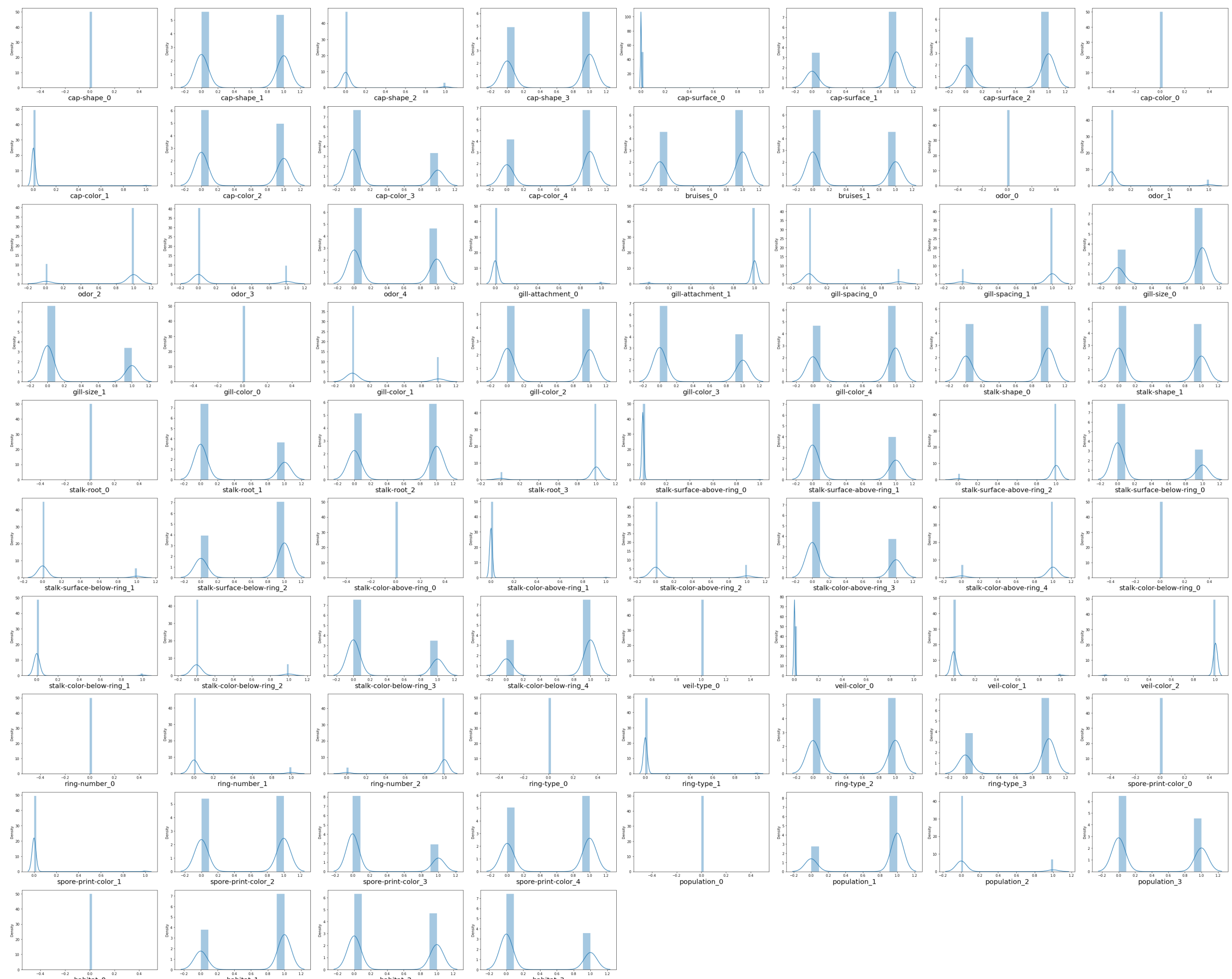
Out[11]:

	cap-shape_0	cap-shape_1	cap-shape_2	cap-shape_3	cap-surface_0	cap-surface_1	cap-surface_2	cap-color_0	cap-color_1	ca color_
0	0	0	0	1	0	0	1	0	0	
1	0	0	0	1	0	0	1	0	0	
2	0	0	1	0	0	0	1	0	0	
3	0	0	0	1	0	1	0	0	0	
4	0	0	0	1	0	0	1	0	0	

Checking for outliers

In [12]:
```python
# Checking outlier
plt.figure(figsize = (50,40))
plotnumber = 1

for column in x:
    if plotnumber <=80:
        ax = plt.subplot(10,8, plotnumber)
        sns.distplot(x[column])
        plt.xlabel(column, fontsize = 20)
    plotnumber +=1
plt.tight_layout()
```



There is no outliers.

Split data into train and test. Model will be bulit on training data and tested on test data.

In [13]:
```python
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25, rando
print('Data has been splited.')
```

```
Data has been splited.
```

Model Building.

Logistic Regression model instantiaing, training and evaluating

In [14]:
```
Lr = LogisticRegression()
Lr.fit(x_train, y_train)
y_pred = Lr.predict(x_test)
```

In [15]:
```
print('-----------------------------------------------------------\n')
print('Confusion Matrix :')
cfm = confusion_matrix(y_test, y_pred)
print(cfm)
print('\n-----------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('-----------------------------------------------------------')
```

```
-----------------------------------------------------------

Confusion Matrix :
[[1056    2]
 [   3  970]]

----------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1058
           1       1.00      1.00      1.00       973

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

------------------------------------------------------------
```

Conclusion : Logistic Regression model has 100% score .

Cross Validation score to check if the model is overfitting

In [16]:
```
cv = cross_val_score(Lr, x, y, cv = 5)
print('Cross Validation score of Logistic Regression model --->', cv.mean())
```

```
Cross Validation score of Logistic Regression model ---> 0.877243956043956
```

Conclusion : Logistic Regression model has 87% Cross Validation score .

Decision Tree model instantiaing, training and evaluating

In [17]:
```
DT = DecisionTreeClassifier()
DT.fit(x_train, y_train)
y_pred = DT.predict(x_test)
```

In [18]:
```
print('-----------------------------------------------------------\n')
print('Confusion Matrix :')
cfm = confusion_matrix(y_test, y_pred)
print(cfm)
print('\n-----------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('-----------------------------------------------------------')
```

```
-----------------------------------------------------------

Confusion Matrix :
[[1058    0]
 [   0  973]]

-----------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1058
           1       1.00      1.00      1.00       973

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

-----------------------------------------------------------
```

Conclusion : Decision Tree model has 100% score .

Cross Validation score to check if the model is overfitting

In [19]:
```
cv = cross_val_score(DT, x, y, cv = 5)
print('Cross Validation score of Decision Tree model --->', cv.mean())
```

```
Cross Validation score of Decision Tree model ---> 0.9280909435392195
```

Conclusion : Decision Tree model has 93% Cross Validation score .

Knn model instantiaing, training and evaluating

In [20]:
```
Knn = KNeighborsClassifier()
Knn.fit(x_train, y_train)
y_pred = Knn.predict(x_test)
```

In [21]:
```
print('------------------------------------------------------------\n')
print('Confusion Matrix :')
cfm = confusion_matrix(y_test, y_pred)
print(cfm)
print('\n------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('------------------------------------------------------------')
```

```
------------------------------------------------------------

Confusion Matrix :
[[1058    0]
 [   0  973]]

------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1058
           1       1.00      1.00      1.00       973

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

------------------------------------------------------------
```

Conclusion : Knn model has 100% score .

Cross Validation score to check if the model is overfitting

In [22]:
```
cv = cross_val_score(Knn, x, y, cv = 5)
print('Cross Validation score of Knn model --->', cv.mean())
```

```
Cross Validation score of Knn model ---> 0.9308065176203109
```

Conclusion : Knn model has 93% Cross Validation score .

Random Forest model instantiaing, training and evaluating

In [23]:
```
Rn = RandomForestClassifier()
Rn.fit(x_train, y_train)
y_pred = Rn.predict(x_test)
```

In [24]:
```
print('-----------------------------------------------------------\n')
print('Confusion Matrix :')
cfm = confusion_matrix(y_test, y_pred)
print(cfm)
print('\n-----------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('-----------------------------------------------------------')
```

```
-----------------------------------------------------------

Confusion Matrix :
[[1058    0]
 [   0  973]]

-----------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1058
           1       1.00      1.00      1.00       973

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

-----------------------------------------------------------
```

Conclusion : Random Forest model has 100% score .

Cross Validation score to check if the model is overfitting

In [25]:
```
cv = cross_val_score(Rn, x, y, cv = 5)
print('Cross Validation score of Knn model --->', cv.mean())
```

```
Cross Validation score of Knn model ---> 0.9209553618794999
```

Conclusion : Random Forest model has 90% Cross Validation score .

SVM model instantiaing, training and evaluating

In [26]:
```
svc = SVC()
svc.fit(x_train, y_train)
y_pred = svc.predict(x_test)
```

In [27]:
```
print('-----------------------------------------------------------\n')
print('Confusion Matrix :')
cfm = confusion_matrix(y_test, y_pred)
print(cfm)
print('\n-----------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('------------------------------------------------------------')
```

```
-----------------------------------------------------------

Confusion Matrix :
[[1058    0]
 [   0  973]]

----------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1058
           1       1.00      1.00      1.00       973

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

------------------------------------------------------------
```

Conclusion : SVM model has 100% score .

Cross Validation score to check if the model is overfitting

In [28]:
```
cv = cross_val_score(svc, x, y, cv = 5)
print('Cross Validation score of Knn model --->', cv.mean())
```

```
Cross Validation score of Knn model ---> 0.8893054945054946
```

Conclusion : SVM model has 88% Cross Validation score .

Looking CV score we found Decision Tree has best model so we do Hyperparameter Tuning on it.

In [29]:
```
# we are tuning hyperparameter, we are passing the different values for both parc
grid_param = {'criterion': ['gini', 'entropy'], 'max_depth': range(2, 20, 3), 'mi
```

In [34]:
```
grid_search = GridSearchCV(estimator = DT, param_grid = grid_param, cv = 5 , n_jc
```

In [35]:
```
grid_search.fit(x_train, y_train)
```

Out[35]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(), n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': range(2, 20, 3),
                         'min_samples_leaf': range(1, 50, 2),
                         'min_samples_split': range(2, 50, 2)})
```

In [36]:
```
best_parameters = grid_search.best_params_
print(best_parameters)
```

```
{'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_spli
t': 2}
```

In [38]:
```
hdt = DecisionTreeClassifier(criterion = 'gini', max_depth = 8 , min_samples_leaf
hdt.fit(x_train, y_train)
hdt.score(x_test, y_test)
```

Out[38]:
```
1.0
```

In [39]:
```
y_pred = hdt.predict(x_test)
```

In [40]:
```python
print('------------------------------------------------------------\n')
print('Confusion Matrix :')
cfm = confusion_matrix(y_test, y_pred)
print(cfm)
print('\n------------------------------------------------------------')
print('\nClassification Report:')
print(classification_report(y_test, y_pred, digits = 2))
print('------------------------------------------------------------')
```

```
------------------------------------------------------------

Confusion Matrix :
[[1058    0]
 [   0  973]]

------------------------------------------------------------

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1058
           1       1.00      1.00      1.00       973

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

------------------------------------------------------------
```

After Hyperparameter Tuning model accuracy score increase to 100% .

Saving The Model

In [42]:
```python
# saving the model to the Local file system
filename = 'hdt_model.pickle'
pickle.dump(hdt, open(filename, 'wb'))
```

Final Conclusion : Decision Tree is our best model.

In [ ]:
```python

```