Seven Supervised Machine Learning Models - Mushroom Classification dataset

Supervised Machine learning models used

- Logistic Regression
- Decision Tree
- K Nearest Neighbor
- Bagging Model
- Random Forest
- Naive Bayes
- Support Vector Machine

Objective

- The objective is to classify whether the mushroom is edible or poisonous by it's various features.

Dataset source & brief

- The dataset has been sourced from Kaggle.
- It includes descriptions of hypothetical samples corresponding to 23 species of gilled mushrooms in the Agaricus and Lepiota Family Mushroom drawn from The Audubon Society Field Guide to North American Mushrooms (1981). Here the target variable is 'class'.

Import the libraries

In [14]:

```
import os
import numpy as np
import pandas as pd

#visualization
import matplotlib.pyplot as plt
import seaborn as sns

#evaluation
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
from sklearn.model_selection import cross_val_score

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

Load and read the dataset

In [15]:

```
df=pd.read_csv(r"C:\Users\manme\Documents\Priya\Stats and ML\Dataset\mushrooms.csv")
df.head()
```

Out[15]:

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

5 rows × 23 columns

Basic info about the dataset

In [16]:

```
df.shape  #check shape
```

Out[16]:

```
(8124, 23)
```

In [17]:

```
df.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
```

In [18]:

```
df.isnull().sum()   # check missing values
```

Out[18]:

```
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
```

In [19]:

```
df.duplicated().sum()  #check duplicate values
```

Out[19]:

```
0
```

In [20]:

```
df.describe().T    #statistical summary
```

Out[20]:

	count	unique	top	freq
class	8124	2	e	4208
cap-shape	8124	6	x	3656
cap-surface	8124	4	y	3244
cap-color	8124	10	n	2284
bruises	8124	2	f	4748
odor	8124	9	n	3528
gill-attachment	8124	2	f	7914
gill-spacing	8124	2	c	6812
gill-size	8124	2	b	5612
gill-color	8124	12	b	1728
stalk-shape	8124	2	t	4608
stalk-root	8124	5	b	3776
stalk-surface-above-ring	8124	4	s	5176
stalk-surface-below-ring	8124	4	s	4936
stalk-color-above-ring	8124	9	w	4464
stalk-color-below-ring	8124	9	w	4384
veil-type	8124	1	p	8124
veil-color	8124	4	w	7924
ring-number	8124	3	o	7488
ring-type	8124	5	p	3968
spore-print-color	8124	9	w	2388
population	8124	6	v	4040
habitat	8124	7	d	3148

In [21]:

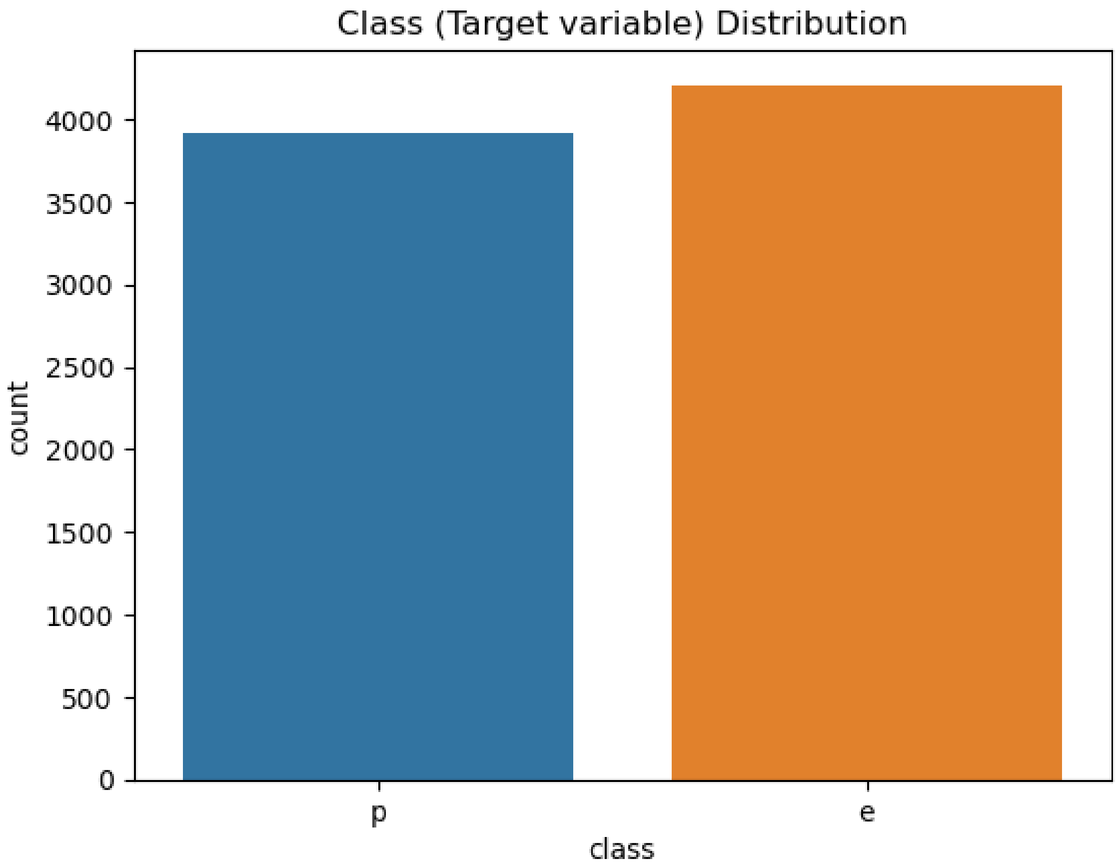
```
df['class'].value_counts()    # check balance of Target variable
```

Out[21]:

```
e    4208
p    3916
Name: class, dtype: int64
```

In [22]:

```
sns.countplot(x='class',  data=df)
plt.title('Class (Target variable) Distribution')
plt.show()
```



In [23]:

```
for i in df.columns:
    print("----------------------", i ,
         "-----------------------")
    print()
    print(set(df[i].tolist()))
    print()
```

```
---------------------- class ----------------------
{'p', 'e'}
---------------------- cap-shape ----------------------
{'f', 'b', 'c', 's', 'k', 'x'}
---------------------- cap-surface ----------------------
{'y', 's', 'f', 'g'}
---------------------- cap-color ----------------------
{'p', 'w', 'b', 'r', 'c', 'g', 'u', 'n', 'y', 'e'}
---------------------- bruises ----------------------
{'t', 'f'}
---------------------- odor ----------------------
{'p', 'f', 'c', 'a', 'l', 's', 'n', 'y', 'm'}
---------------------- gill-attachment ----------------------
{'a', 'f'}
---------------------- gill-spacing ----------------------
{'w', 'c'}
---------------------- gill-size ----------------------
{'b', 'n'}
---------------------- gill-color ----------------------
{'p', 'o', 'h', 'w', 'b', 'r', 'g', 'k', 'u', 'n', 'y', 'e'}
---------------------- stalk-shape ----------------------
{'t', 'e'}
---------------------- stalk-root ----------------------
{'b', 'r', 'c', '?', 'e'}
---------------------- stalk-surface-above-ring ----------------------
{'y', 's', 'f', 'k'}
---------------------- stalk-surface-below-ring ----------------------
{'y', 's', 'f', 'k'}
---------------------- stalk-color-above-ring ----------------------
{'p', 'o', 'w', 'b', 'c', 'g', 'n', 'y', 'e'}
---------------------- stalk-color-below-ring ----------------------
```

```
{'p', 'o', 'w', 'b', 'c', 'g', 'n', 'y', 'e'}

---------------------- veil-type ----------------------

{'p'}

---------------------- veil-color ----------------------

{'w', 'y', 'o', 'n'}

---------------------- ring-number ----------------------

{'o', 't', 'n'}

---------------------- ring-type ----------------------

{'p', 'f', 'l', 'n', 'e'}

---------------------- spore-print-color ----------------------

{'o', 'h', 'w', 'b', 'r', 'k', 'u', 'n', 'y'}

---------------------- population ----------------------

{'v', 'c', 'a', 's', 'n', 'y'}

---------------------- habitat ----------------------

{'p', 'w', 'd', 'g', 'l', 'u', 'm'}
```

In [24]:

```
# Dropping 'veil-type' as it has only one unique value
df=df.drop(['veil-type'],axis=1)
```

Encoding

In [25]:

```
# encode categorical columns
from sklearn.preprocessing import LabelEncoder
df=df.apply(LabelEncoder().fit_transform)
df.head()
```

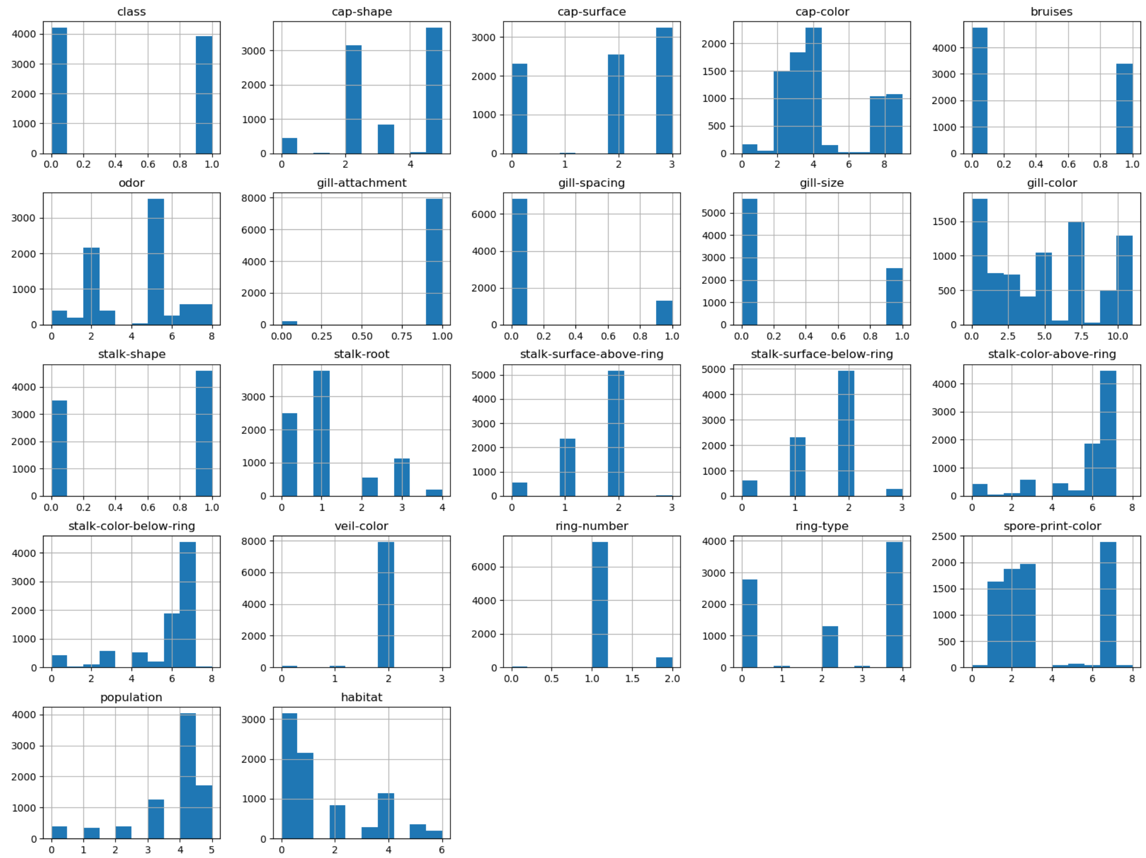
Out[25]:

	class	cap-shape	cap-surface	cap-color	bruises	odor	gill-attachment	gill-spacing	gill-size	gill-color	...	stalk surface above ring
0	1	5	2	4	1	6	1	0	1	4	...	2
1	0	5	2	9	1	0	1	0	0	4	...	2
2	0	0	2	8	1	3	1	0	0	5	...	2
3	1	5	3	8	1	6	1	0	1	5	...	2
4	0	5	2	3	0	5	1	1	0	4	...	2

5 rows × 22 columns

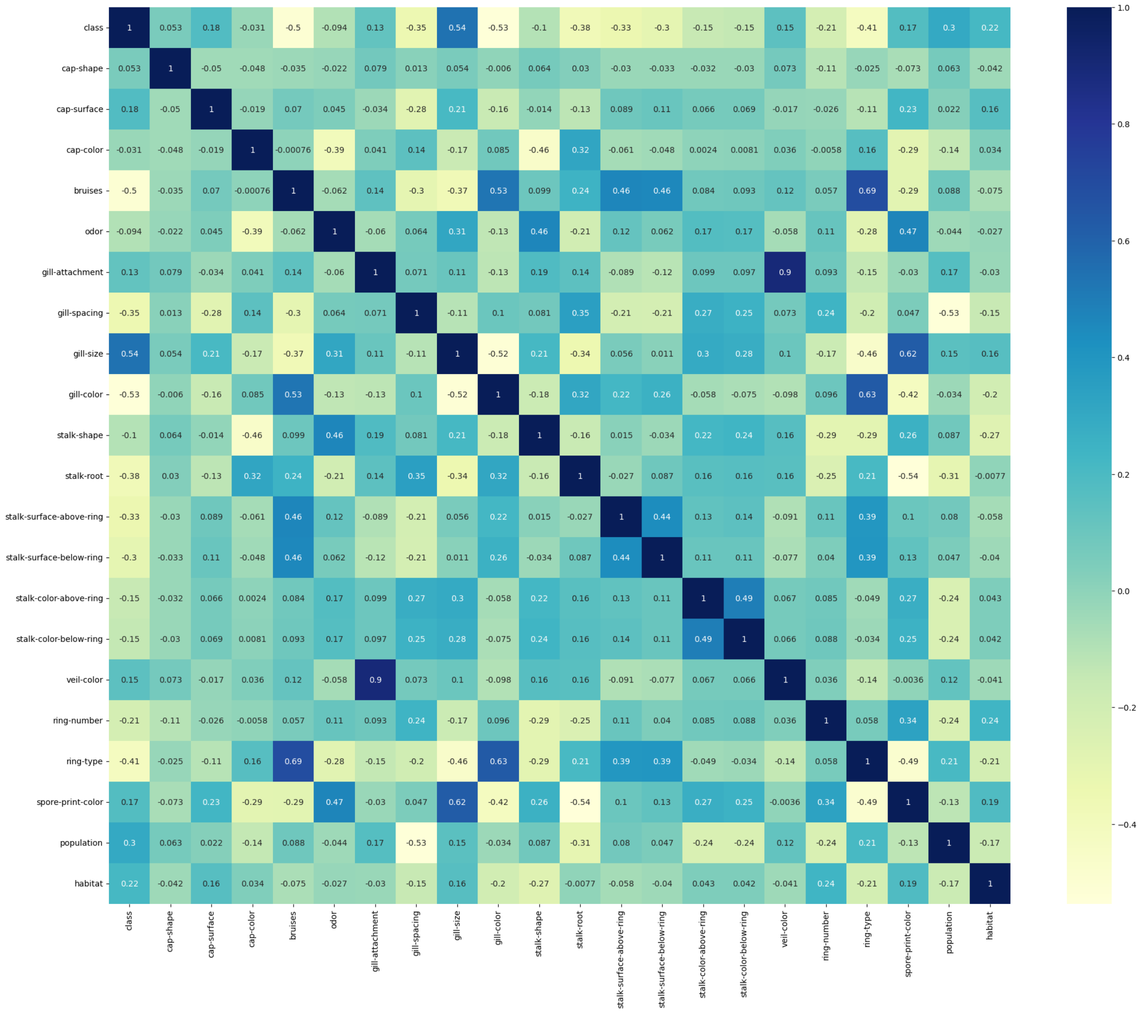
In [26]:

```
df.hist(figsize=(20,15))
plt.show()
```



In [27]:

```
plt.figure(figsize=(25,20))
sns.heatmap(df.corr(),annot=True,cmap='YlGnBu')  # Correlation by using Heatmap
plt.show()
```



Data Splitting

In [28]:

```
# Split data into independent and dependent
x = df.drop(['class'],axis=1)
y = df[['class']]
```

In [29]:

```
x.head(2)
```

Out[29]:

	cap-shape	cap-surface	cap-color	bruises	odor	gill-attachment	gill-spacing	gill-size	gill-color	stalk-shape	...	stalk-surface-above-rin
0	5	2	4	1	6	1	0	1	4	0	...	
1	5	2	9	1	0	1	0	0	4	0	...	

2 rows × 21 columns

In [30]:

```
y.head(2)
```

Out[30]:

	class
0	1
1	0

Feature Scaling

In [31]:

```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
fs=sc.fit_transform(x)
pd.DataFrame(fs).head()
```

Out[31]:

	0	1	2	3	4	5	6	7	
0	1.029712	0.140128	-0.198250	1.185917	0.881938	0.162896	-0.438864	1.494683	-0.228
1	1.029712	0.140128	1.765874	1.185917	-1.970316	0.162896	-0.438864	-0.669038	-0.228
2	-2.087047	0.140128	1.373049	1.185917	-0.544189	0.162896	-0.438864	-0.669038	0.053
3	1.029712	0.953270	1.373049	1.185917	0.881938	0.162896	-0.438864	1.494683	0.053
4	1.029712	0.140128	-0.591075	-0.843230	0.406562	0.162896	2.278612	-0.669038	-0.228

5 rows × 21 columns

In [32]:

```
# Split data into Train & Test data
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2,random_state=0)
```

In [33]:

```
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

Out[33]:

```
((6499, 21), (1625, 21), (6499, 1), (1625, 1))
```

Building Model

1. Logistic Regression Model

In [34]:

```
# Model building
from sklearn.linear_model import LogisticRegression
logit = LogisticRegression(random_state=100)
logit.fit(x_train, y_train)

# Predict
y_pred_train_logit = logit.predict(x_train)
y_pred_test_logit = logit.predict(x_test)

# Evaluate
print('Logistic regression - Train accuracy:', accuracy_score(y_train, y_pred_train_logi
print('---------------'*5)
print('Logistic regression - Test accuracy:', accuracy_score(y_test, y_pred_test_logit))
```

```
Logistic regression - Train accuracy: 0.9518387444222188
---------------------------------------------------------------------------
-
Logistic regression - Test accuracy: 0.955076923076923
```

In [35]:

```
# Cross validation
training_accuracy = cross_val_score(logit,x_train, y_train, cv=10)
test_accuracy = cross_val_score(logit,x_test, y_test, cv=10)
print('Logistic regression after Cross validation Train accuracy:', training_accuracy.me
print('---------------'*5)
print('Logistic regression after Cross validation Test accuracy:', test_accuracy.mean())
```

```
Logistic regression after Cross validation Train accuracy: 0.9504541898779
187
---------------------------------------------------------------------------
-
Logistic regression after Cross validation Test accuracy: 0.94341816253881
7
```

Conclusion - Logistic Regression

- Logistic regression both Train & Test accuracy is coming at 95%.
- Though after Cross validation Train accuracy is coming at 95% & Test accuracy at 94%.

2. Decision Tree Model

In [36]:

```
# Model building
from sklearn.tree import DecisionTreeClassifier,plot_tree
dtree=DecisionTreeClassifier(criterion ='gini')
dtree.fit(x_train,y_train)

#Predict
y_pred_train_dtree=dtree.predict(x_train)
y_pred_test_dtree=dtree.predict(x_test)

# Evaluate
print('Decision Tree - Train accuracy:', accuracy_score(y_train, y_pred_train_dtree))
print('---------------'*5)
print('Decision Tree - Test accuracy:', accuracy_score(y_test, y_pred_test_dtree))
```

```
Decision Tree - Train accuracy: 1.0
---------------------------------------------------------------------------
-
Decision Tree - Test accuracy: 1.0
```

Feature importance

In [37]:

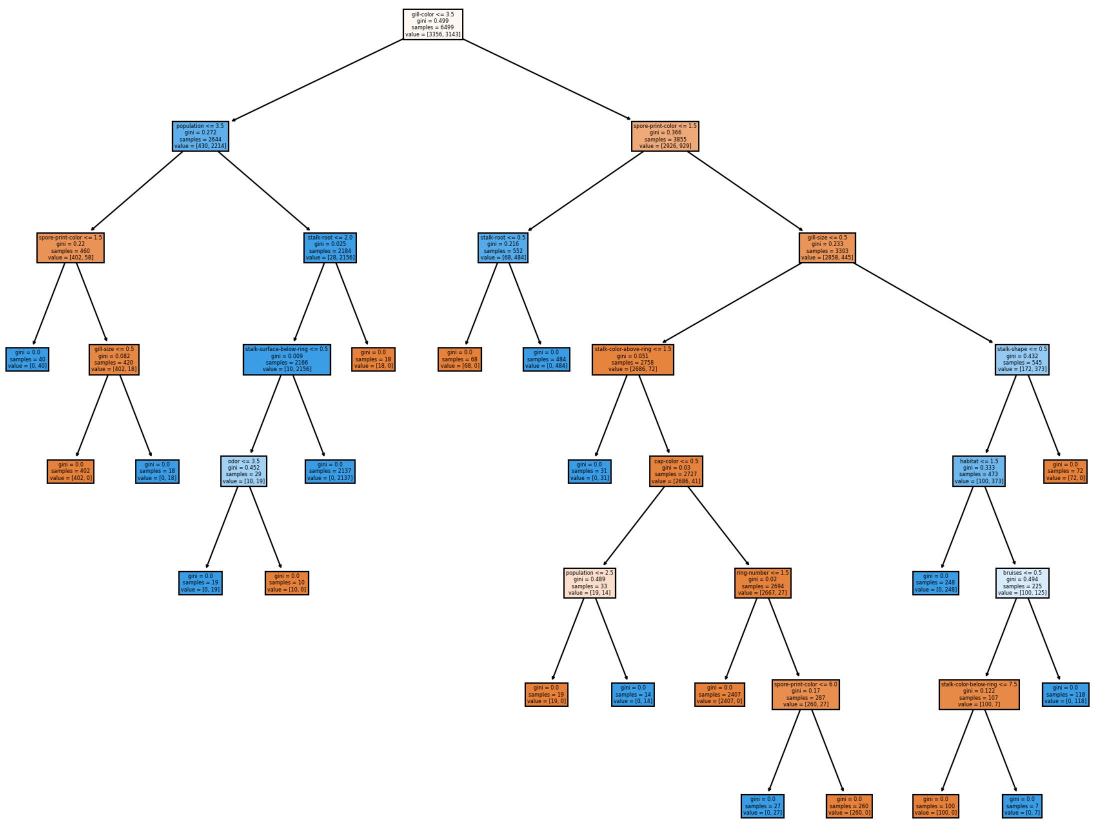
```
# Check Feature importance
dtree.feature_importances_
pd.DataFrame(index=x.columns,data=dtree.feature_importances_, columns=['Feature Importan
```

Out[37]:

	Feature Importance
cap-shape	0.000000
cap-surface	0.000000
cap-color	0.003446
bruises	0.030199
odor	0.004037
gill-attachment	0.000000
gill-spacing	0.000000
gill-size	0.132124
gill-color	0.343691
stalk-shape	0.023943
stalk-root	0.047634
stalk-surface-above-ring	0.000000
stalk-surface-below-ring	0.002096
stalk-color-above-ring	0.018322
stalk-color-below-ring	0.004031
veil-color	0.000000
ring-number	0.001398
ring-type	0.000000
spore-print-color	0.196162
population	0.178558
habitat	0.014358

In [38]:

```
#Visualization
from sklearn.tree import plot_tree
plt.figure(figsize=(15,12),dpi=150)
plot_tree(dtree,filled=True,feature_names=x.columns)
plt.show()
```



In [39]:

```
# Using Post prunning method to handle overfitting probelm
def report_model(model):
    model_preds=model.predict(x_test)
    print(classification_report(y_test,model_preds))
    print('\n')
    plt.figure(figsize=(15,12),dpi=150)
    plot_tree(model,filled=True,feature_names=x.columns)
plt.show()
```

In [40]:

```
# max depth at 4
prunned_dtree=DecisionTreeClassifier(max_depth=4)
prunned_dtree.fit(x_train,y_train)
```

Out[40]:

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=4)
```

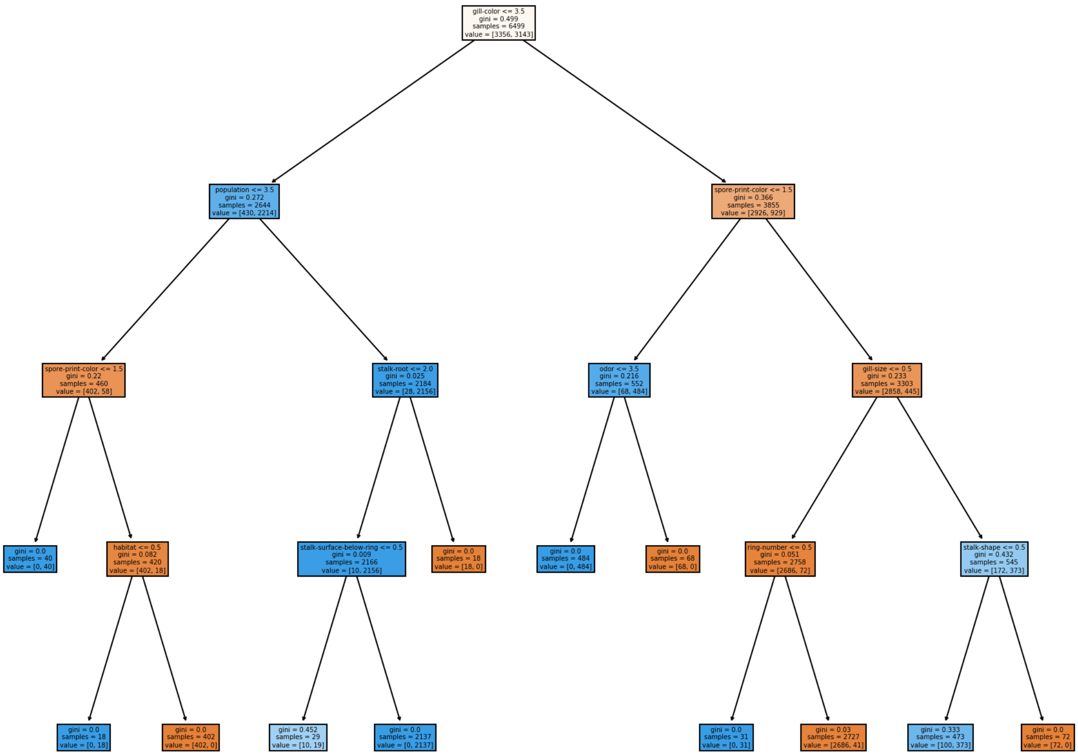
In [41]:

```
report_model(prunned_dtree)
```

```
              precision    recall  f1-score   support

           0       0.99      0.97      0.98       852
           1       0.97      0.99      0.98       773

    accuracy                           0.98      1625
   macro avg       0.98      0.98      0.98      1625
weighted avg       0.98      0.98      0.98      1625
```



In [42]:

```
y_pred_prunned_train=prunned_dtree.predict(x_train)
y_pred_prunned_test=prunned_dtree.predict(x_test)

print('Decision Tree post prunning- Train accuracy:',accuracy_score(y_train,y_pred_prunn
print('---------------'*5)
print('Decision Tree post prunning- Test accuracy:', accuracy_score(y_test,y_pred_prunne
```

```
Decision Tree post prunning- Train accuracy: 0.9767656562548084
---------------------------------------------------------------------------
-
Decision Tree post prunning- Test accuracy: 0.9821538461538462
```

Conclusion - Decision Tree

- Both Train and Test accuracy is coming at 100% before prunning which shows it has overfitting problem.
- After giving max depth of 4, post prunning train data accuracy is of 97% and test data accuracy of 98% thus solving the problem of overfitting.

3. K Nearest Neighbor Model

In [43]:

```
# Model building
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier()
knn.fit(x_train, y_train)

y_pred_train_knn = knn.predict(x_train)
y_pred_test_knn = knn.predict(x_test)

print('K Nearest Neighbor - Train accuracy:', accuracy_score(y_train, y_pred_train_knn))
print('---------------'*5)
print('K Nearest Neighbor - Test accuracy:', accuracy_score(y_test, y_pred_test_knn))
```

```
K Nearest Neighbor - Train accuracy: 0.9996922603477458
----------------------------------------------------------------------------
-
K Nearest Neighbor - Test accuracy: 0.9969230769230769
```

In [44]:

```
# Cross validation
training_accuracy = cross_val_score(knn,x_train, y_train, cv=10)
test_accuracy = cross_val_score(knn,x_test, y_test, cv=10)
print('K Nearest Neighbor after Cross validation Train accuracy:', training_accuracy.mea
print('---------------'*5)
print('K Nearest Neighbor after Cross validation Test accuracy:', test_accuracy.mean())
```

```
K Nearest Neighbor after Cross validation Train accuracy: 0.99815337205167
72
----------------------------------------------------------------------------
-
K Nearest Neighbor after Cross validation Test accuracy: 0.985253351511020
2
```

Conclusion - K Nearest Neighbor

- K Nearest Neigbor both Train & Test accuracy is coming at 99%.
- After Cross validation Train accuracy remains same & Test accuracy is at 98%

4. Bagging Model

In [45]:

```
# Model building
from sklearn.ensemble import BaggingClassifier
bagging=BaggingClassifier()
bagging.fit(x_train,y_train)# Predict

#Predict
y_pred_train_bag=bagging.predict(x_train)
y_pred_test_bag=bagging.predict(x_test)

# Evaluate
print('Bagging - Train accuracy:', accuracy_score(y_train, y_pred_train_bag))
print('---------------'*5)
print('Bagging - Test accuracy:', accuracy_score(y_test, y_pred_test_bag))
```

```
Bagging - Train accuracy: 1.0
---------------------------------------------------------------------------
-
Bagging - Test accuracy: 1.0
```

In [46]:

```
# Cross validation
training_accuracy = cross_val_score(bagging,x_train, y_train, cv=10)
test_accuracy = cross_val_score(bagging,x_test, y_test, cv=10)
print('Bagging after Cross validation Train accuracy:', training_accuracy.mean())
print('---------------'*5)
print('Bagging after Cross validation Test accuracy:', test_accuracy.mean())
```

```
Bagging after Cross validation Train accuracy: 1.0
---------------------------------------------------------------------------
-
Bagging after Cross validation Test accuracy: 0.9987692191168673
```

Conclusion - Bagging

- Bagging both Train & Test accuracy is coming at 100% which means it has overfitting problem.
- After Cross validation Train accuracy remains same & Test accuracy is at 99%.

5. Random Forest Model

In [47]:

```
# Model building
from sklearn.ensemble import RandomForestClassifier
rf=RandomForestClassifier(n_estimators=200,oob_score=False)
rf.fit(x_train,y_train)

# Predict
y_pred_train_rf=rf.predict(x_train)
y_pred_test_rf=rf.predict(x_test)

# Evaluate
print('Random Forest - Train accuracy:', accuracy_score(y_train, y_pred_train_rf))
print('---------------'*5)
print('Random Forest - Test accuracy:', accuracy_score(y_test, y_pred_test_rf))
```

```
Random Forest - Train accuracy: 1.0
--------------------------------------------------------------------------
-
Random Forest - Test accuracy: 1.0
```

In [48]:

```
### Cross validation as it has overfitting problem
training_accuracy = cross_val_score(rf, x_train, y_train, cv=10)
test_accuracy = cross_val_score(rf, x_test, y_test, cv=10)
print('Random Forest after Cross validation Train accuracy:', training_accuracy.mean())
print('---------------'*5)
print('Random Forest after Cross validation Test accuracy:', test_accuracy.mean())
```

```
Random Forest after Cross validation Train accuracy: 1.0
--------------------------------------------------------------------------
-
Random Forest after Cross validation Test accuracy: 0.9993827160493828
```

Conclusion - Random Forest

- Random Forest is yielding the same result as Bagging model

6. Naive Bayes Model

In [49]:

```
# Model building
from sklearn.naive_bayes import GaussianNB
gnb = GaussianNB()
gnb.fit(x_train, y_train)

# Predict the model
y_pred_train_gnb = gnb.predict(x_train)
y_pred_test_gnb = gnb.predict(x_test)

# Evaluate
print('Naive Bayes -Train accuracy:', accuracy_score(y_train, y_pred_train_gnb))
print('---------------'*5)
print('Naive Bayes -Test accuracy:', accuracy_score(y_test, y_pred_test_gnb))
```

```
Naive Bayes -Train accuracy: 0.9222957378058163
--------------------------------------------------------------------------
-
Naive Bayes -Test accuracy: 0.9156923076923077
```

In [50]:

```
# Cross validation
training_accuracy = cross_val_score(gnb,x_train, y_train, cv=10)
test_accuracy = cross_val_score(gnb,x_test, y_test, cv=10)
print('Naive Bayes after Cross validation Train accuracy:', training_accuracy.mean())
print('---------------'*5)
print('Naive Bayes after Cross validation Test accuracy:', test_accuracy.mean())
```

```
Naive Bayes after Cross validation Train accuracy: 0.9224494488562286
--------------------------------------------------------------------------
-
Naive Bayes after Cross validation Test accuracy: 0.8811255017798987
```

Conclusion - Gaussian Naive Bayes

- In Gaussian Naive Bayes model Train accuracy is coming at 92% and Test accuracy at 91%.
- After Cross validation Train accuracy is coming at 92% and Test accuracy at 88%.

7. Support Vector Machine Model

In [51]:

```
# a. Radial Basis Function Kernel (RBF) - (Defaut SVM) Model building
from sklearn.svm import SVC
svm_rbf = SVC(kernel='rbf')
svm_rbf.fit(x_train, y_train)


#Predict
y_pred_train_rbf = svm_rbf.predict(x_train)
y_pred_test_rbf = svm_rbf.predict(x_test)

#Evaluate
print('Rbf - SVM - Train accuracy:', accuracy_score(y_train, y_pred_train_rbf))
print('------------------------'*5)
print('Rbf - SVM - Test accuracy:', accuracy_score(y_test, y_pred_test_rbf))
```

```
Rbf - SVM - Train accuracy: 0.9910755500846284
--------------------------------------------------------------------------
----------------------------------------------
Rbf - SVM - Test accuracy: 0.9907692307692307
```

In [52]:

```
# Cross validation
train_accuracy = cross_val_score(svm_rbf, x_train, y_train, cv=10)
test_accuracy = cross_val_score(svm_rbf, x_test, y_test, cv=10)
print('Rbf - SVM after Cross validation Train accuracy:', train_accuracy.mean())
print('------------------------'*5)
print('Rbf - SVM after Cross validation Test accuracy:', test_accuracy.mean())
```

```
Rbf - SVM after Cross validation Train accuracy: 0.989536328078701
--------------------------------------------------------------------------
----------------------------------------------
Rbf - SVM after Cross validation Test accuracy: 0.9649587215026887
```

Conclusion - SVM- Rbf

- In SVM - Rbf both Train & Test accuracy is coming at 99%
- After Cross validation Train accuracy is coming at 98% & Test accuracy at 96%.

In [53]:

```
# b. Linear Kernel Model building
svm_linear = SVC(kernel='linear')
svm_linear.fit(x_train, y_train)

#Predict
y_pred_train_linear = svm_linear.predict(x_train)
y_pred_test_linear = svm_linear.predict(x_test)

#Evaluate
print('Linear - SVM- Train accuracy:', accuracy_score(y_train, y_pred_train_linear))
print('------------------------'*5)
print('Linear - SVM- Test accuracy:', accuracy_score(y_test, y_pred_test_linear))
```

```
Linear - SVM- Train accuracy: 0.9804585320818587
--------------------------------------------------------------------------
----------------------------------------------
Linear - SVM- Test accuracy: 0.9809230769230769
```

In [54]:

```
# Cross validation
train_accuracy = cross_val_score(svm_linear, x_train, y_train, cv=10)
test_accuracy = cross_val_score(svm_linear, x_test, y_test, cv=10)
print('Linear - SVM after Cross validation Train accuracy:', train_accuracy.mean())
print('------------------------'*5)
print('Linear - SVM after Cross validation Test accuracy:', test_accuracy.mean())
```

```
Linear - SVM after Cross validation Train accuracy: 0.9679945478250565
--------------------------------------------------------------------------
----------------------------------------------
Linear - SVM after Cross validation Test accuracy: 0.9440127243808225
```

Conclusion - SVM- Linear

- In SVM- Linear both Train & Test accuracy is coming at 98%
- After Cross validation Train accuracy is coming at 96% & Test accuracy at 94%.

In [55]:

```
# c. Polynomial Kernel Model building
svm_poly = SVC(kernel='poly')
svm_poly.fit(x_train, y_train)


#Predict
y_pred_train_poly = svm_poly.predict(x_train)
y_pred_test_poly = svm_poly.predict(x_test)


#Evaluate
print('Polynomial - SVM- Train accuracy:', accuracy_score(y_train, y_pred_train_poly))
print('------------------------'*5)
print('Polynomial - SVM- Test accuracy:', accuracy_score(y_test, y_pred_test_poly))
```

```
Polynomial - SVM- Train accuracy: 0.9987690413909832
--------------------------------------------------------------------------
----------------------------------------------
Polynomial - SVM- Test accuracy: 0.9981538461538462
```

In [56]:

```
# Cross validation
train_accuracy = cross_val_score(svm_poly, x_train, y_train, cv=10)
test_accuracy = cross_val_score(svm_poly, x_test, y_test, cv=10)
print('Polynomial - SVM after Cross validation Train accuracy:', train_accuracy.mean())
print('------------------------'*5)
print('Polynomial - SVM after Cross validation Test accuracy:', test_accuracy.mean())
```

```
Polynomial - SVM after Cross validation Train accuracy: 0.9983076923076923
--------------------------------------------------------------------------
----------------------------------------------
Polynomial - SVM after Cross validation Test accuracy: 0.9883132621373931
```

Conclusion - SVM- Polynomial

- In SVM - Polynomial both Train & Test accuracy is coming at 99%
- After Cross validation Train accuracy is coming at 99% & Test accuracy at 98%.

Voting ensemble

- Voting is an ensemble method that combines the performances of multiple models to make predictions.
- In classification problems, there are two types of voting: hard voting and soft voting.
- Hard voting entails picking the prediction with the highest number of votes, whereas soft voting entails combining the probabilities of each prediction in each model and picking the prediction with the highest total probability.

In [57]:

```
from sklearn.ensemble import VotingClassifier
```

In [58]:

```
estimators = [('Logistic',logit),('Decision_tree', dtree),('KNN',knn),('Bagging',bagging
              ('NaiveBayes',gnb), ('SVM_RBF' ,svm_rbf),('SVM_Linear',svm_linear),('SVM_P
```

In [59]:

```
voting = VotingClassifier(estimators = estimators, voting='hard')
voting.fit(x_train, y_train)
```

Out[59]:

```
▸                                                                    VotingCl
         Logistic           Decision_tree                 KNN               Ba
▸                      ▸                       ▸                       ▸
LogisticRegression     DecisionTreeClassifier  KNeighborsClassifier    Bagging
```

In [60]:

```
y_pred_train_voting = voting.predict(x_train)
y_pred_test_voting = voting.predict(x_test)
```

In [61]:

```
print('Voting ensemble train accuracy:', accuracy_score(y_train, y_pred_train_voting))
print('---------------'*5)
print('Voting ensemble train accuracy:', accuracy_score(y_test, y_pred_test_voting))
```

```
Voting ensemble train accuracy: 0.9987690413909832
--------------------------------------------------------------------------
-
Voting ensemble train accuracy: 0.9987692307692307
```

Conclusion - Voting Ensemble

- Voting ensemble yielded train & test accuracy of 99%.

Final Conclusion -

- In Logistic regression model both Train & Test accuracy is coming at 95%. After Cross validation Train accuracy is coming at 95% & Test accuracy at 94%
- In Decision Tree model both Train and Test accuracy is coming at 100% before prunning which shows it has overfitting problem. After giving max depth of 4, post prunning train data accuracy is 97% and test data accuracy is 98% thus solving the problem of overfitting.
- In K Nearest Neigbor model both Train & Test accuracy is coming at 99%. After Cross validation Train accuracy remains same & Test accuracy is 98%.
- In Bagging model both Train & Test accuracy is coming at 100% which means it has overfitting problem. After Cross validation Train accuracy remains same & Test accuracy is at 99% which means overfitting problem still persists.
- Random Forest model is yielding the same result as Bagging model.

- In Gaussian Naive Bayes model Train accuracy is coming at 92% and Test accuracy at 91%. After Cross validation Train accuracy is coming at 92% and Test accuracy at 88%.
- In Support Vector machine model I applied 3 different kernels- Rbf, Linear & Polynomial.
  - In SVM - Rbf both Train & Test accuracy is coming at 99%. After Cross validation Train accuracy is coming at 98% & Test accuracy at 96%.
  - In SVM- Linear both Train & Test accuracy is coming at 98%. After Cross validation Train accuracy is coming at 96% & Test accuracy at 94%.
  - In SVM - Polynomial both Train & Test accuracy is coming at 99%. After Cross validation Train accuracy is coming at 99% & Test accuracy at 98%.
- Voting ensemble yielded train & test accuracy of 99%.
- In all the above models except Gaussian Naive Bayes model both Train & Test data accuracy is coming over 90% against the commonly taken threshold accuracy value of 70%.
- In some models overfitting problem still persists.
- There is less than 10% accuracy variation between train & Test accuracy thus making almost all of them good model.
- So we can say that the above model solves our objective which is to classify whether the mushroom is edible or poisonous

In [ ]:

```

```