Mushroom Classification

In [1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from ucimlrepo import fetch_ucirepo
from sklearn.cluster import KMeans
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay

random_state = np.random.seed(12)
pd.set_option('display.max_columns', None)
```

1 - Obtaining the Initial Dataset

In [2]:
```python
mushrooms_dataset = fetch_ucirepo(id=73)
```

In [3]:
```python
initial_features = mushrooms_dataset.data.features
initial_targets = mushrooms_dataset.data.targets

processed_features = initial_features.copy()
processed_targets = initial_targets.copy()
```

In [4]:
```python
initial_features
```

Out[4]:

	cap-shape	cap-surface	cap-color	bruises	odor	gill-attachment	gill-spacing	gill-size	gill-color	stalk-shape	stalk-root	stalk-surface-above-ring	stalk-surface-below-ring	stalk-color-above-ring	stalk-color-below-ring	veil typ
0	x	s	n	t	p	f	c	n	k	e	e	s	s	w	w	p
1	x	s	y	t	a	f	c	b	k	e	c	s	s	w	w	p
2	b	s	w	t	l	f	c	b	n	e	c	s	s	w	w	p
3	x	y	w	t	p	f	c	n	n	e	e	s	s	w	w	p
4	x	s	g	f	n	f	w	b	k	t	e	s	s	w	w	p
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	.
8119	k	s	n	f	n	a	c	b	y	e	NaN	s	s	o	o	p
8120	x	s	n	f	n	a	c	b	y	e	NaN	s	s	o	o	p
8121	f	s	n	f	n	a	c	b	n	e	NaN	s	s	o	o	p
8122	k	y	n	f	y	f	c	n	b	t	NaN	s	k	w	w	p
8123	x	s	n	f	n	a	c	b	y	e	NaN	s	s	o	o	p

8124 rows × 22 columns

In [5]:
```python
initial_targets
```

Out[5]:

	poisonous
0	p
1	e
2	e
3	p
4	e
...	...
8119	e
8120	e
8121	e
8122	p
8123	e

8124 rows × 1 columns

2 - Processing the Dataset

2.1 - Processing Ordinal Categorical Feature Values

In [6]:
```
def ordinal(initial, key, values):
    data = initial.copy()
    data[key] = initial[key].apply(lambda value: values.index(value))
    return data
```

2.1.1 - Gill-Spacing

- c = close -> 0
- w = crowded -> 1
- d = distant -> 2

In [7]:
```
print(f"Initial Value Counts\n{processed_features['gill-spacing'].value_counts()}\n")
processed_features = ordinal(processed_features, 'gill-spacing', ['c', 'w', 'd'])
print(f"Final Value Counts\n{processed_features['gill-spacing'].value_counts()}")
```

```
Initial Value Counts
gill-spacing
c    6812
w    1312
Name: count, dtype: int64

Final Value Counts
gill-spacing
0    6812
1    1312
Name: count, dtype: int64
```

2.1.2 - Gill-Size

- n = narrow -> 0
- b = broad -> 1

In [8]:
```
print(f"Initial Value Counts\n{processed_features['gill-size'].value_counts()}\n")
processed_features = ordinal(processed_features, 'gill-size', ['n', 'b'])
print(f"Final Value Counts\n{processed_features['gill-size'].value_counts()}")
```

```
Initial Value Counts
gill-size
b    5612
n    2512
Name: count, dtype: int64

Final Value Counts
gill-size
1    5612
0    2512
Name: count, dtype: int64
```

2.1.3 - Ring-Number

- n = none -> 0
- o = one -> 1
- t = two -> 2

In [9]:
```
print(f"Initial Value Counts\n{processed_features['ring-number'].value_counts()}\n")
processed_features = ordinal(processed_features, 'ring-number', ['n', 'o', 't'])
print(f"Final Value Counts\n{processed_features['ring-number'].value_counts()}")
```

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

Final Value Counts
ring-number
1    7488
2     600
0      36
Name: count, dtype: int64
```

2.1.4 - Population

- y = solitary -> 0

- v = several -> 1
- s = scattered -> 2
- n = numerous -> 3
- c = clustered -> 4
- a = abundant -> 5

In [10]:
```
print(f"Initial Value Counts\n{processed_features['population'].value_counts()}\n")
processed_features = ordinal(processed_features, 'population', ['y', 'v', 's', 'n', 'c', 'a'])
print(f"Final Value Counts\n{processed_features['population'].value_counts()}")
```

```
Initial Value Counts
population
v    4040
y    1712
s    1248
n     400
a     384
c     340
Name: count, dtype: int64

Final Value Counts
population
1    4040
0    1712
2    1248
3     400
5     384
4     340
Name: count, dtype: int64
```

2.2 - Processing Non-Ordinal Categorical Feature Values

In [11]:
```
def non_ordinal(initial, key, values):
    data = initial.copy()
    for value in values:
        data[f"{value}-{key}"] = (initial[key] == value).astype(int)
    data.drop([key], axis=1, inplace=True)
    return data
```

2.2.1 - Cap-Shape

- b = bell
- c = conical
- x = convex
- f = flat
- k = knobbed
- s = sunken

In [12]:
```
processed_features = non_ordinal(processed_features, 'cap-shape', ['b', 'c', 'x', 'f', 'k', 's'])
```

2.2.2 - Cap-Surface

- f = fibrous
- g = grooves
- y = scaly
- s = smooth

In [13]:
```
processed_features = non_ordinal(processed_features, 'cap-surface', ['f', 'g', 'y', 's'])
```

2.2.3 - Cap-Colour

- n = brown
- b = buff
- c = cinnamon
- g = gray
- r = green
- p = pink
- u = purple
- e = red
- w = white
- y = yellow

In [14]:
```
processed_features = non_ordinal(processed_features, 'cap-color', ['n', 'b', 'c', 'g', 'r', 'p', 'u', 'e', 'w', 'y'])
```

2.2.4 - Bruises

- t = bruises
- f = no bruises

In [15]:
```
processed_features = non_ordinal(processed_features, 'bruises', ['t', 'f'])
```

2.2.5 - Odour

- a = almond
- l = anise
- c = creosote
- y = fishy
- f = foul
- m = musty
- n = none
- p = pungent
- s = spicy

In [16]:
```
processed_features = non_ordinal(processed_features, 'odor', ['a', 'l', 'c', 'y', 'f', 'm', 'n', 'p', 's'])
```

2.2.6 - Gill-Attachment

- a = attached
- d = descending
- f = free
- n = notched

In [17]:
```
processed_features = non_ordinal(processed_features, 'gill-attachment', ['a', 'd', 'f', 'n'])
```

2.2.7 - Gill-Colour

- k = black
- n = brown
- b = buff
- h = chocolate
- g = gray
- r = green
- o = orange
- p = pink
- u = purple
- e = red
- w = white
- y = yellow

In [18]:
```
processed_features = non_ordinal(processed_features, 'gill-color', ['k', 'n', 'b', 'h', 'g', 'r', 'o', 'p', 'u', 'e', 'w',
```

2.2.8 - Stalk-Shape

- e = enlarging
- t = tapering

In [19]:
```
processed_features = non_ordinal(processed_features, 'stalk-shape', ['e', 't'])
```

2.2.9 - Stalk-Root

- b = bulbous
- c = club
- u = cup
- e = equal
- z = rhizomorphs
- r = rooted

In [20]:
```
processed_features = non_ordinal(processed_features, 'stalk-root', ['b', 'c', 'u', 'e', 'z', 'r'])
```

2.2.10 - Stalk-Surface-Above-Ring

- f = fibrous
- y = scaly

- k = silky
- s = smooth

In [21]:
```
processed_features = non_ordinal(processed_features, 'stalk-surface-above-ring', ['f', 'y', 'k', 's'])
```

2.2.11 - Stalk-Surface-Below-Ring

- f = fibrous
- y = scaly
- k = silky
- s = smooth

In [22]:
```
processed_features = non_ordinal(processed_features, 'stalk-surface-below-ring', ['f', 'y', 'k', 's'])
```

2.2.12 - Stalk-Colour-Above-Ring

- n = brown
- b = buff
- c = cinnamon
- g = gray
- o = orange
- p = pink
- e = red
- w = white
- y = yellow

In [23]:
```
processed_features = non_ordinal(processed_features, 'stalk-color-above-ring', ['n', 'b', 'c', 'g', 'o', 'p', 'e', 'w', 'y
```

2.2.13 - Stalk-Colour-Below-Ring

- n = brown
- b = buff
- c = cinnamon
- g = gray
- o = orange
- p = pink
- e = red
- w = white
- y = yellow

In [24]:
```
processed_features = non_ordinal(processed_features, 'stalk-color-below-ring', ['n', 'b', 'c', 'g', 'o', 'p', 'e', 'w', 'y
```

2.2.14 - Veil-Type

- p = partial
- u = universal

In [25]:
```
processed_features = non_ordinal(processed_features, 'veil-type', ['p', 'u'])
```

2.2.15 - Veil-Colour

- n = brown
- o = orange
- w = white
- y = yellow

In [26]:
```
processed_features = non_ordinal(processed_features, 'veil-color', ['n', 'o', 'w', 'y'])
```

2.2.16 - Ring-Type

- c = cobwebby
- e = evanescent
- f = flaring
- l = large
- n = none
- p = pendant
- s = sheathing
- z = zone

In [27]:
```python
processed_features = non_ordinal(processed_features, 'ring-type', ['c', 'e', 'f', 'l', 'n', 'p', 's', 'z'])
```

2.2.17 - Spore-Print-Colour

- k = black
- n = brown
- b = buff
- h = chocolate
- r = green
- o = orange
- u = purple
- w = white
- y = yellow

In [28]:
```python
processed_features = non_ordinal(processed_features, 'spore-print-color', ['k', 'n', 'b', 'h', 'r', 'o', 'u', 'w', 'y'])
```

2.2.18 - Habitat

- g = grasses
- l = leaves
- m = meadows
- p = paths
- u = urban
- w = waste
- d = woods

In [29]:
```python
processed_features = non_ordinal(processed_features, 'habitat', ['g', 'l', 'm', 'p', 'u', 'w', 'd'])
```

2.3 - Validating the Processed Feature Values

In [30]:
```python
print("Shape =", initial_features.shape)
initial_features
```

```
Shape = (8124, 22)
```

Out[30]:

	cap-shape	cap-surface	cap-color	bruises	odor	gill-attachment	gill-spacing	gill-size	gill-color	stalk-shape	stalk-root	stalk-surface-above-ring	stalk-surface-below-ring	stalk-color-above-ring	stalk-color-below-ring	veil-typ
0	x	s	n	t	p	f	c	n	k	e	e	s	s	w	w	p
1	x	s	y	t	a	f	c	b	k	e	c	s	s	w	w	p
2	b	s	w	t	l	f	c	b	n	e	c	s	s	w	w	p
3	x	y	w	t	p	f	c	n	n	e	e	s	s	w	w	p
4	x	s	g	f	n	f	w	b	k	t	e	s	s	w	w	p
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
8119	k	s	n	f	n	a	c	b	y	e	NaN	s	s	o	o	p
8120	x	s	n	f	n	a	c	b	y	e	NaN	s	s	o	o	p
8121	f	s	n	f	n	a	c	b	n	e	NaN	s	s	o	o	p
8122	k	y	n	f	y	f	c	n	b	t	NaN	s	k	w	w	p
8123	x	s	n	f	n	a	c	b	y	e	NaN	s	s	o	o	p

8124 rows × 22 columns

In [31]:
```python
print("Shape =", processed_features.shape)
processed_features
```

```
Shape = (8124, 115)
```

Out[31]:

	gill-spacing	gill-size	ring-number	population	b-cap-shape	c-cap-shape	x-cap-shape	f-cap-shape	k-cap-shape	s-cap-shape	f-cap-surface	g-cap-surface	y-cap-surface	s-cap-surface	n-cap-color	b cap colo
0	0	0	1	2	0	0	1	0	0	0	0	0	0	1	1	
1	0	1	1	3	0	0	1	0	0	0	0	0	0	1	0	
2	0	1	1	3	1	0	0	0	0	0	0	0	0	1	0	
3	0	0	1	2	0	0	1	0	0	0	0	0	1	0	0	
4	1	1	1	5	0	0	1	0	0	0	0	0	0	1	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
8119	0	1	1	4	0	0	0	0	1	0	0	0	0	1	1	
8120	0	1	1	1	0	0	1	0	0	0	0	0	0	1	1	
8121	0	1	1	4	0	0	0	1	0	0	0	0	0	1	1	
8122	0	0	1	1	0	0	0	0	1	0	0	0	1	0	1	
8123	0	1	1	4	0	0	1	0	0	0	0	0	0	1	1	

8124 rows × 115 columns

2.4 - Processing Binary Target Values

In [32]:

```
print(f"Initial Value Counts\n{processed_targets['poisonous'].value_counts()}\n")
processed_targets = ordinal(processed_targets, 'poisonous', ['e', 'p'])
print(f"Final Value Counts\n{processed_targets['poisonous'].value_counts()}")
```

```
Initial Value Counts
poisonous
e    4208
p    3916
Name: count, dtype: int64

Final Value Counts
poisonous
0    4208
1    3916
Name: count, dtype: int64
```

2.5 - Validating the Processed Target Values

In [33]:

```
print("Shape =", initial_targets.shape)
initial_targets
```

```
Shape = (8124, 1)
```

Out[33]:

	poisonous
0	p
1	e
2	e
3	p
4	e
...	...
8119	e
8120	e
8121	e
8122	p
8123	e

8124 rows × 1 columns

In [34]:

```
print("Shape =", processed_targets.shape)
processed_targets
```

```
Shape = (8124, 1)
```

Out[34]:

	poisonous
0	1
1	0
2	0
3	1
4	0
...	...
8119	0
8120	0
8121	0
8122	1
8123	0

8124 rows × 1 columns

3 - Splitting the Dataset

In [35]:
```
split_proportion = 0.7
dataset_size = processed_features.shape[0]
train_size = int(dataset_size * split_proportion)
test_size = dataset_size - train_size
```

In [36]:
```
x_train, y_train = processed_features.iloc[train_size:], processed_targets.iloc[train_size:]['poisonous']
x_test, y_test = processed_features.iloc[:train_size], processed_targets.iloc[:train_size]['poisonous']

print(f"Shape of x_train = {x_train.shape}")
print(f"Shape of y_train = {y_train.shape}")
print(f"Shape of x_test = {x_test.shape}")
print(f"Shape of y_test = {y_test.shape}")
```

```
Shape of x_train = (2438, 115)
Shape of y_train = (2438,)
Shape of x_test = (5686, 115)
Shape of y_test = (5686,)
```

4 - Supervised Model

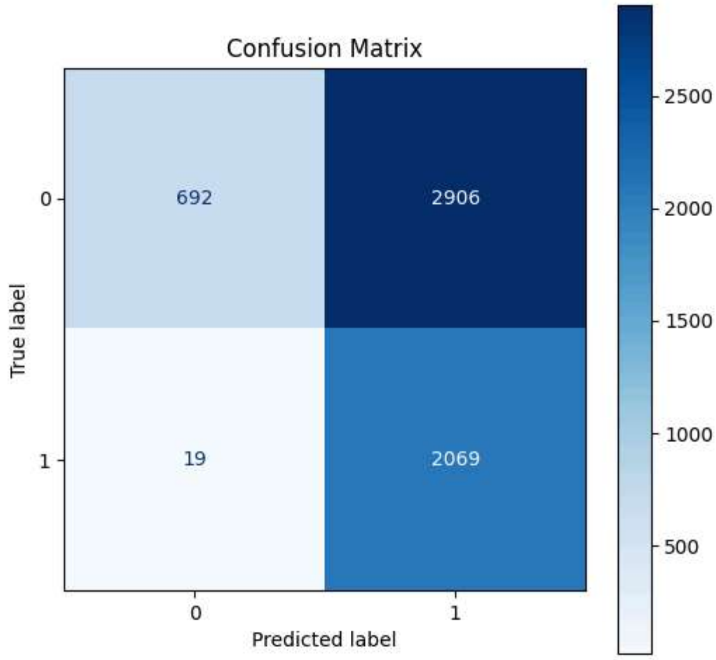
Accuracy = 0.48558

In [37]:
```
def display_results(accuracy, confusion_matrix, classification_report, predictions):
    print(f"Accuracy = {accuracy:.5f}\n")

    fig, ax = plt.subplots(figsize=(6, 6))
    disp = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix, display_labels=np.unique(predictions))
    disp.plot(ax=ax, cmap='Blues', values_format='d')
    plt.title("Confusion Matrix")
    plt.show()

    print(classification_report)
```

In [38]:
```
def train_test_eval(model, x_train_set, y_train_set, x_test_set, y_test_set):
    model.fit(x_train_set, y_train_set)
    y_pred_set = model.predict(x_test_set).astype(int)
    results = (y_pred_set == y_test_set).value_counts()
    accuracy = float(results[True] / y_test_set.shape[0])
    return {
        "predictions": y_pred_set,
        "accuracy": accuracy,
        "confusion_matrix": confusion_matrix(y_test_set, y_pred_set),
        "classification_report": classification_report(y_test_set, y_pred_set)
    }
```

In [51]:
```
logistic_regression_model = LogisticRegression(n_jobs=-1)
logistic_regression_results = train_test_eval(logistic_regression_model, x_train, y_train, x_test, y_test)
display_results(**logistic_regression_results)
```

```
Accuracy = 0.48558
```



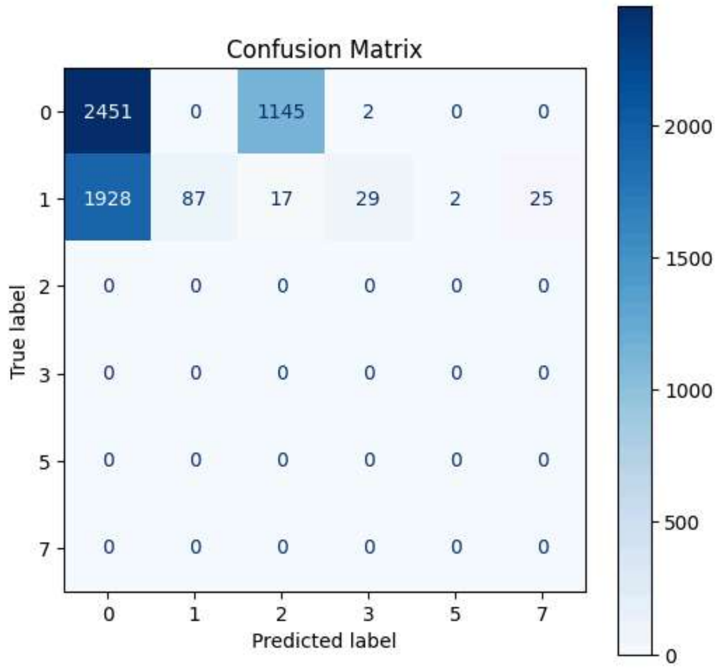

```
              precision    recall  f1-score   support

           0       0.97      0.19      0.32      3598
           1       0.42      0.99      0.59      2088

    accuracy                           0.49      5686
   macro avg       0.69      0.59      0.45      5686
weighted avg       0.77      0.49      0.42      5686
```

5 - Unsupervised Model

Accuracy = 0.44636

In [50]:
```
k_means_model = KMeans()
k_means_results = train_test_eval(k_means_model, x_train, y_train, x_test, y_test)
display_results(**k_means_results)
```

```
Accuracy = 0.44636
```



	precision	recall	f1-score	support
0	0.56	0.68	0.61	3598
1	1.00	0.04	0.08	2088
2	0.00	0.00	0.00	0
3	0.00	0.00	0.00	0
5	0.00	0.00	0.00	0
7	0.00	0.00	0.00	0
accuracy			0.45	5686
macro avg	0.26	0.12	0.12	5686
weighted avg	0.72	0.45	0.42	5686