Project Topic

This project explores the application of supervised learning techniques to classify mushrooms as either **edible** or **poisonous**. This is a **binary classification problem** as the task is to predict one of two discrete classes.

The primary goal of this project is to:

1. Demonstrate the process of supervised learning by applying multiple machine learning algorithms to a real-world classification task.
2. Learn and implement advanced techniques such as hyperparameter tuning, feature engineering, and model evaluation.
3. Showcase performance metrics and comparisons to determine the most effective model for the task.
4. Highlight the importance of accurate classification in practical scenarios, such as identifying potentially dangerous mushrooms.

Data

The dataset used is the **Secondary Mushroom Dataset** from the UCI Machine Learning Repository.

> Dua, D., & Graff, C. (2019). UCI Machine Learning Repository [Secondary Mushroom Dataset]. Retrieved from https://archive.ics.uci.edu/dataset/848/secondary+mushroom+datase.

This dataset was curated as a simulated dataset for binary classification tasks, specifically focusing on the edibility of mushrooms based on their features. It provides diverse feature types and a large number of samples, making it suitable for exploring advanced machine learning techniques and evaluating model performance comprehensively.

The data is sourced into this notebook using the `ucimlrepo` package.

Data Description

- **Number of Samples:** 61,068
- **Number of Features:** 20
- **Feature Types:**
  - Categorical features (e.g., cap shape, surface, color, etc.)
  - Continuous features (e.g., numerical indicators for specific measurements: cap diameter, stem height & width)
- **Task Type:** Binary classification (edible or poisonous)

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from ucimlrepo import fetch_ucirepo
```

```python
# Thanks, UCI_ML_Repo!
# fetch dataset
secondary_mushroom = fetch_ucirepo(id=848)
# data (as pandas dataframes)
X = secondary_mushroom.data.features
y = secondary_mushroom.data.targets

# metadata
# print(secondary_mushroom.metadata)
# variable information
print(secondary_mushroom.variables)
```

```
                    name     role         type demographic description
units  \
0                  class   Target  Categorical        None        None
None
1           cap-diameter  Feature   Continuous        None        None
None
2              cap-shape  Feature  Categorical        None        None
None
3            cap-surface  Feature  Categorical        None        None
None
4              cap-color  Feature  Categorical        None        None
None
5   does-bruise-or-bleed  Feature  Categorical        None        None
None
6        gill-attachment  Feature  Categorical        None        None
None
7           gill-spacing  Feature  Categorical        None        None
None
8             gill-color  Feature  Categorical        None        None
None
9            stem-height  Feature   Continuous        None        None
None
10            stem-width  Feature   Continuous        None        None
None
11             stem-root  Feature  Categorical        None        None
None
12          stem-surface  Feature  Categorical        None        None
None
13            stem-color  Feature  Categorical        None        None
None
14             veil-type  Feature  Categorical        None        None
None
15            veil-color  Feature  Categorical        None        None
None
16              has-ring  Feature  Categorical        None        None
None
17             ring-type  Feature  Categorical        None        None
None
```

```
18     spore-print-color  Feature  Categorical        None        None
None
19               habitat  Feature  Categorical        None        None
None
20                season  Feature  Categorical        None        None
None

   missing_values
0              no
1              no
2              no
3             yes
4              no
5              no
6             yes
7             yes
8              no
9              no
10             no
11            yes
12            yes
13             no
14            yes
15            yes
16             no
17            yes
18            yes
19             no
20             no

'''
Exploratory Data Analysis [Part 1]

The variable information printed above shows that several features
were missing values.
In order to not out right break certain my logisitic regression model
or to degrade performance of my other models,
I inspected the percentage of samples missing the particular features.
I decided to remove features with more than 30% of values missing
to avoid causing collinearity among the features (e.g., associating a
missing veil-type with poisonous if by chance
many poisonous records were missing a veil-type, etc.).
For the rest with missing values I added a new, unique value (?) to
represent missing. This was a viable option because the features
in scope were all categorical instead of continuous.
'''

missing_proportions = X.isnull().mean() * 100
missing_features = missing_proportions[missing_proportions >
0].sort_values(ascending=False)
```

```python
print("Missing values (%) from source dataset:")
print(missing_features)
print('Cleaning data...', end='\n\n')

features_to_drop = missing_proportions[missing_proportions > 30].index
X_cleaned = X.drop(columns=features_to_drop)

features_to_mod = missing_proportions[missing_proportions <= 30].index
for f in features_to_mod:
    X_cleaned.fillna({ f: "?" }, inplace=True)

missing_proportions_check = X_cleaned.isnull().mean() * 100
missing_features_check =
missing_proportions_check[missing_proportions_check > 0]
assert len(missing_features_check) == 0, 'Data is not cleaned as
expected'
X = X_cleaned
print('Data is clean and ready to explore, train, and test!')
print(X.head())
```

```
Missing values (%) from source dataset:
veil-type            94.797688
spore-print-color    89.595376
veil-color           87.861272
stem-root            84.393064
stem-surface         62.427746
gill-spacing         41.040462
cap-surface          23.121387
gill-attachment      16.184971
ring-type             4.046243
dtype: float64
Cleaning data...

Data is clean and ready to explore, train, and test!
   cap-diameter cap-shape cap-surface cap-color does-bruise-or-
bleed  \
0         15.26         x           g         o                    f

1         16.60         x           g         o                    f

2         14.07         x           g         o                    f

3         14.17         f           h         e                    f

4         14.64         x           h         o                    f


  gill-attachment gill-color  stem-height  stem-width stem-color has-
ring  \
0                e          w        16.95       17.09          w
```

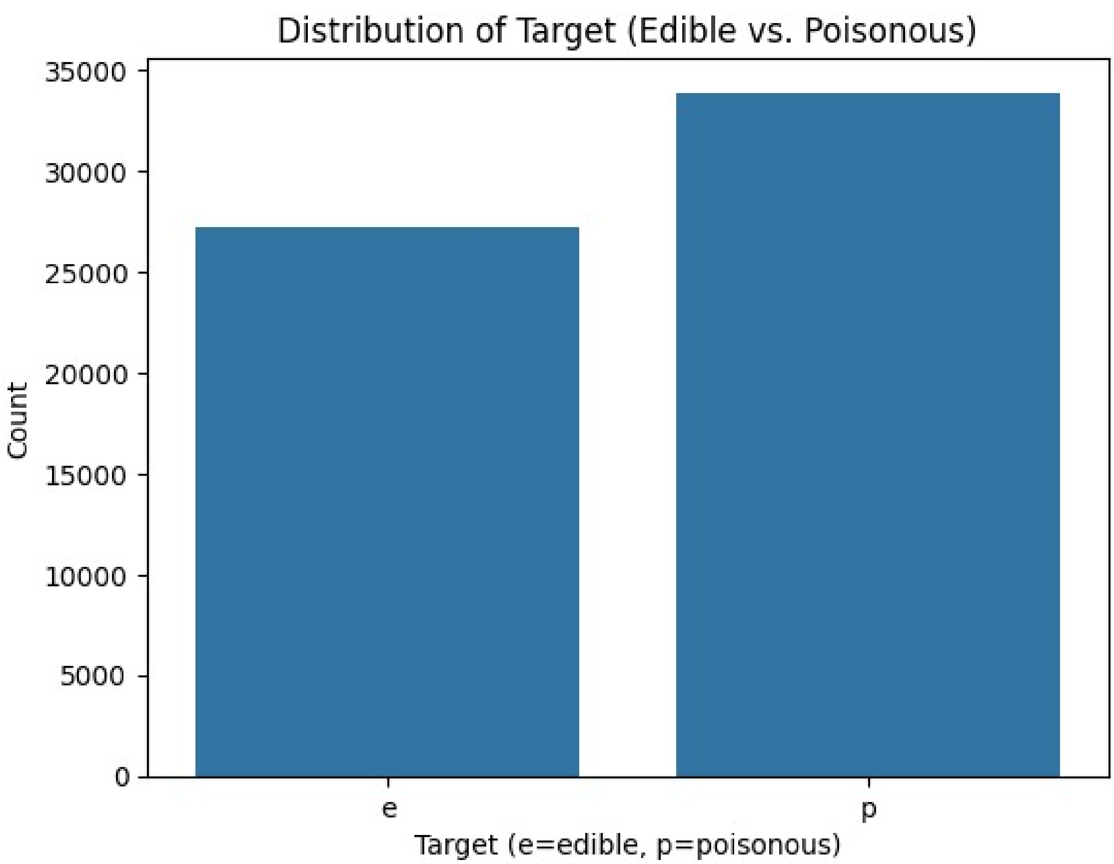
```
t
1                e          w        17.99       18.19            w
t
2                e          w        17.80       17.74            w
t
3                e          w        15.77       15.98            w
t
4                e          w        16.53       17.20            w
t

  ring-type habitat season
0         g       d      w
1         g       d      u
2         g       d      w
3         p       d      w
4         p       d      w
```

```
'''
Exploratory Data Analysis [Part 2]

First, I graphed the distribution of the target class to check whether
the dataset is well balanced between edible and poisonous
samples. A balanced dataset allows me to split my test and training
samples without worrying about one class dominating the other.

Next, I used a correlation matrix, boxplots, and countplots to assess
whether any strong multicollinearity exists between the
features and to evaluate the importance of each feature individually.
Since the dataset is composed primarily of categorical features,
I first encoded those feature values into numeric values. This allowed
me to display a correlation matrix, which showed almost
no significant correlations. However, this lack of correlations might
be due to the nature of the label encoding applied to the
categorical features. Because of the label encoding and the potential
for feature multicollinearity, I hypothesized that my
logistic regression model (see the "Models" section below) would
perform the worst among the models I tested.

The boxplots (used for numerical features) and countplots (used for
categorical features) provided more insightful observations.
The three numerical features exhibited a similar distribution of
values across each feature, with a general trend that large outliers
were typically associated with edible samples. However, since most
values overlapped between classes, I predicted that the numerical
features would not be the most influential in the models. I reached a
similar conclusion for the more balanced categorical features.

However, among the categorical features, several stood out based on
their countplots as being likely to have significant predictive
importance. Specifically, cap-surface, gill-attachment, gill-color,
```

```
and stem-color appeared to be particularly important features.

'''
None #Disable cell output

print(type(y))
y_col = y.iloc[:, 0]
print(type(y_col))
```

```
<class 'pandas.core.frame.DataFrame'>
<class 'pandas.core.series.Series'>
```

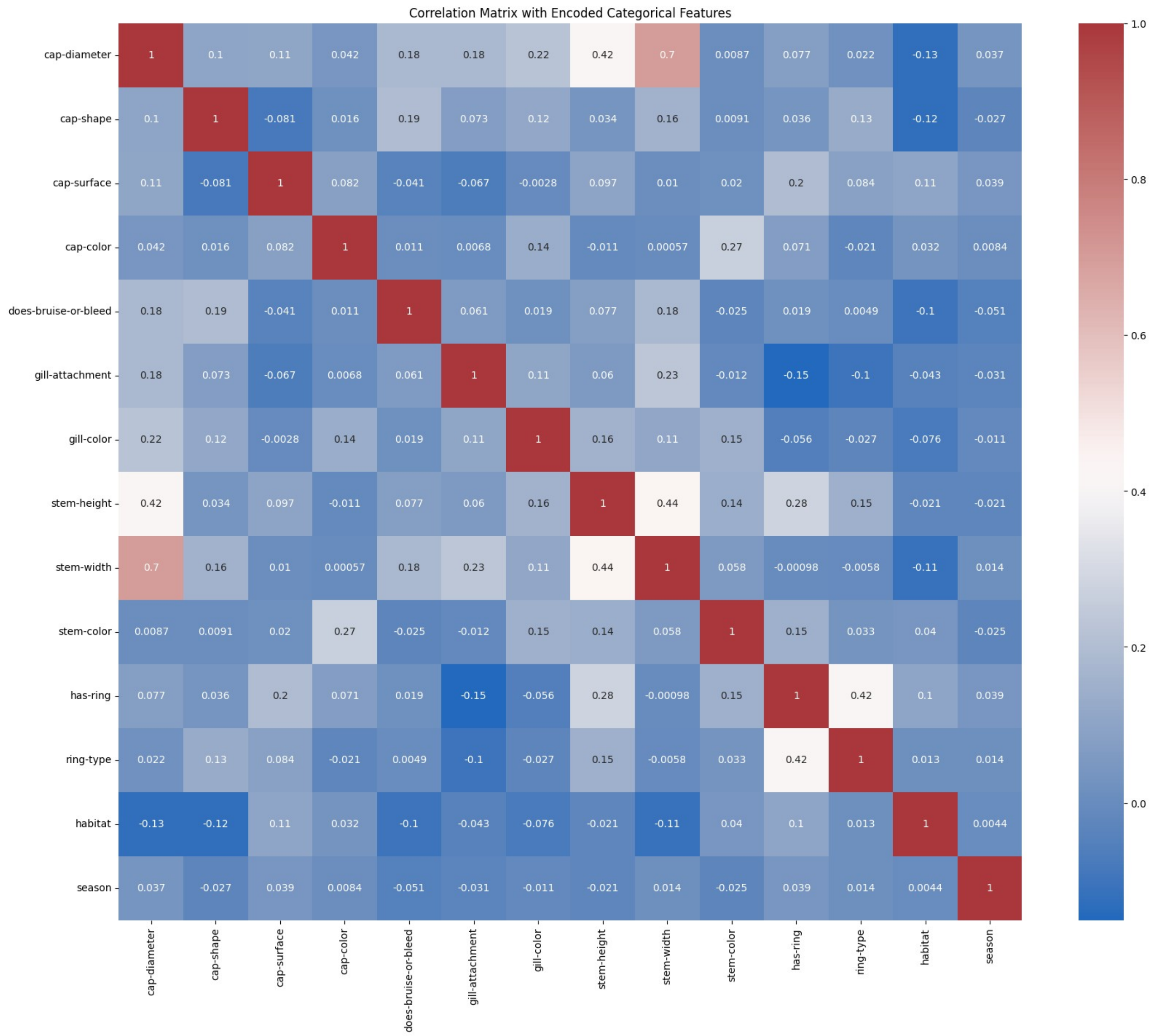
```
sns.countplot(x=y_col, order=['e', 'p'])
plt.title("Distribution of Target (Edible vs. Poisonous)")
plt.xlabel("Target (e=edible, p=poisonous)")
plt.ylabel("Count")
plt.show()
```



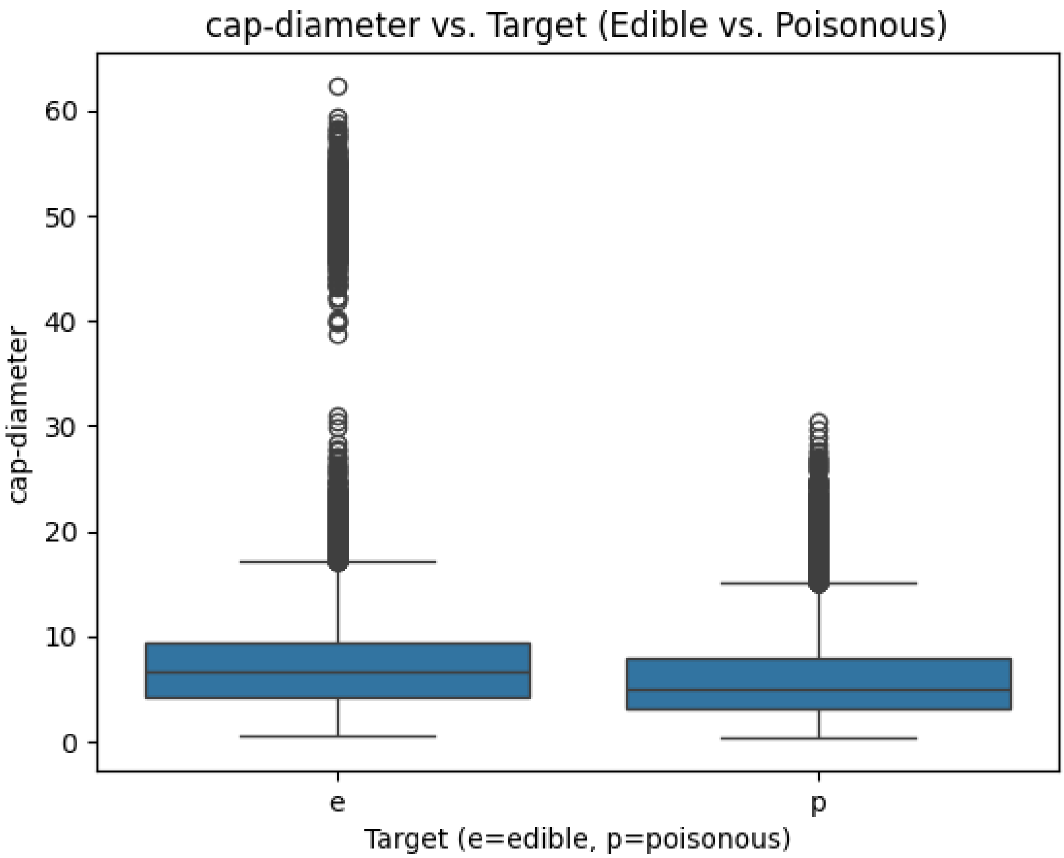

```
num_features = X.select_dtypes(include=['float64'])
cat_features = X.select_dtypes(include=['object'])
print(f'{len(num_features.columns)} numeric features')
print(f'{len(cat_features.columns)} categorical features')
```

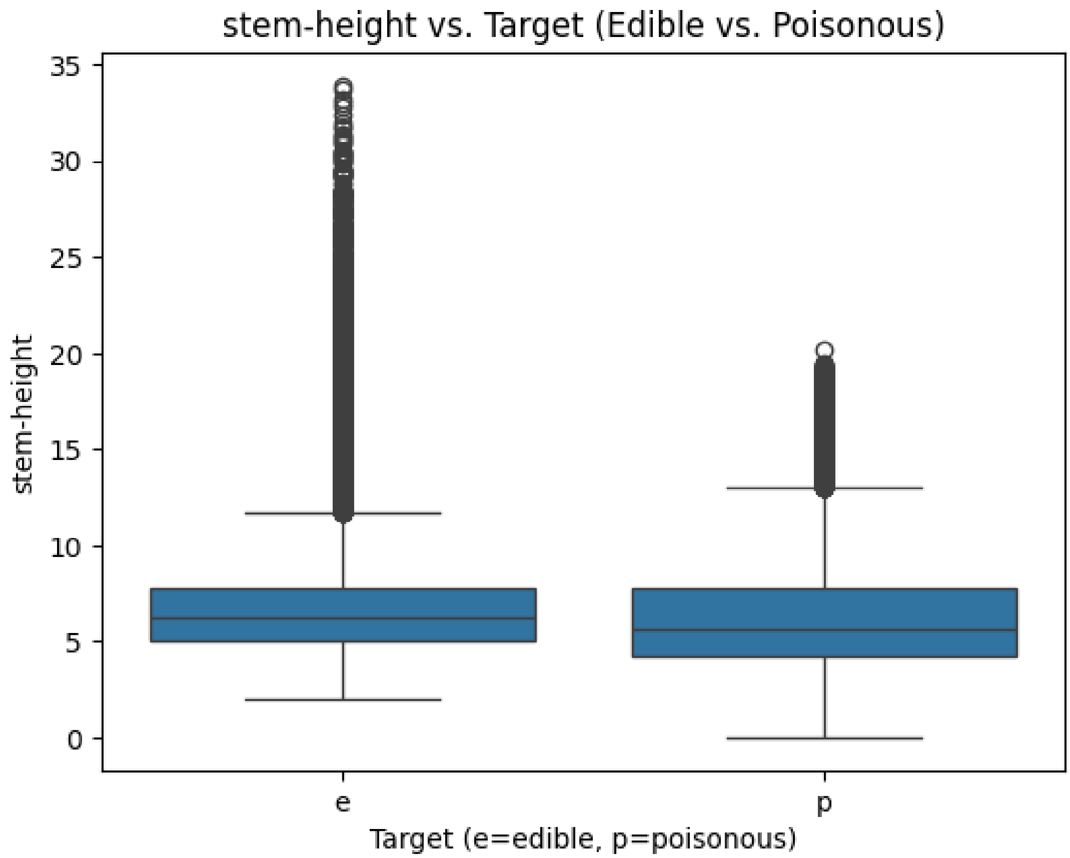
```
3 numeric features
11 categorical features
```

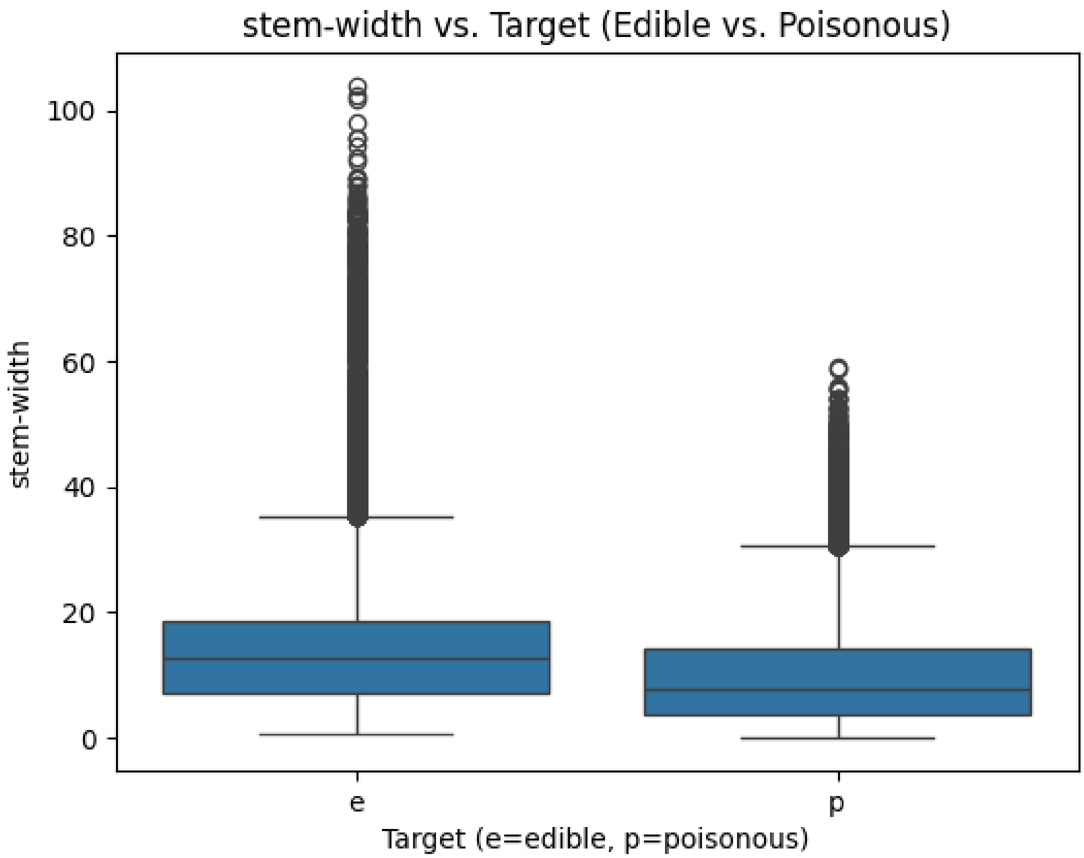
```
from sklearn.preprocessing import LabelEncoder

def label_encode_data(data, le_map):
    clone = data.copy()
    for col in clone.select_dtypes(include=['object']):
        le = LabelEncoder()
        clone[col] = le.fit_transform(clone[col])
        le_map[col] = le
    return clone, le_map

def label_decode_data(data, le_map):
    clone = data.copy()
    for col, le in le_map.items():
        clone[col] = le.inverse_transform(clone[col])
    return clone

X_le, X_le_map = label_encode_data(X, {})
plt.figure(figsize=(20,16))
sns.heatmap(X_le.corr(), cmap='vlag', annot=True)
plt.title("Correlation Matrix with Encoded Categorical Features")
plt.show()
```



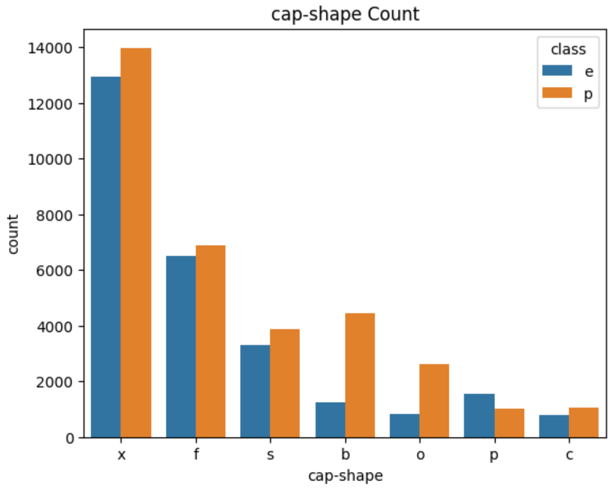

```python
for f in num_features:
    sns.boxplot(x=y_col, y=f, data=X, order=['e', 'p'])
    plt.title(f + ' vs. Target (Edible vs. Poisonous)')
    plt.xlabel('Target (e=edible, p=poisonous)')
    plt.show()
```

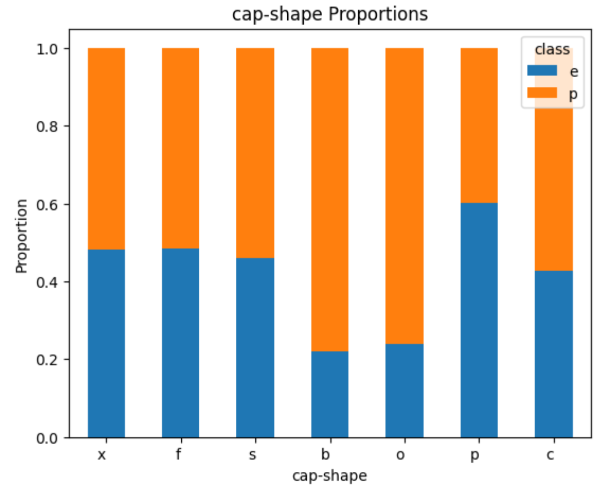

cap-diameter vs. Target (Edible vs. Poisonous)
cap-diameter
60
50
40
30
20
10
0
e
p
Target (e=edible, p=poisonous)

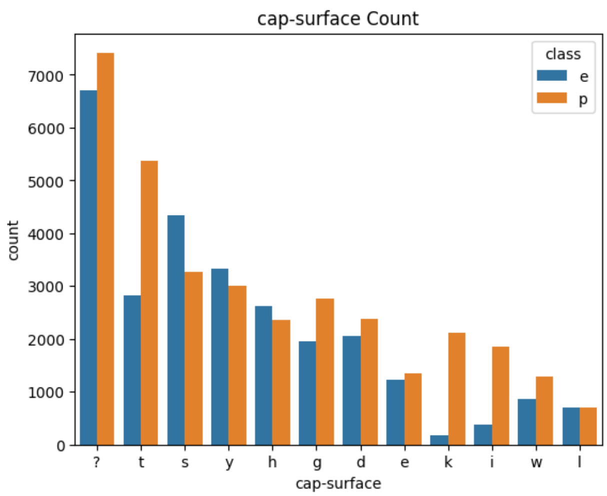

stem-height vs. Target (Edible vs. Poisonous)
stem-height
35
30
25
20
15
10
5
0
e
p
Target (e=edible, p=poisonous)

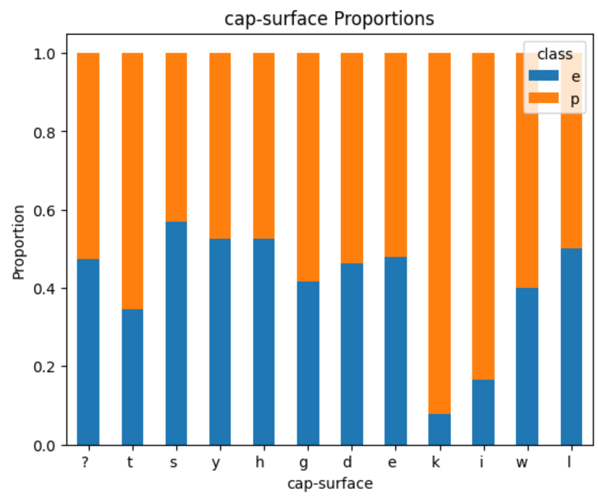


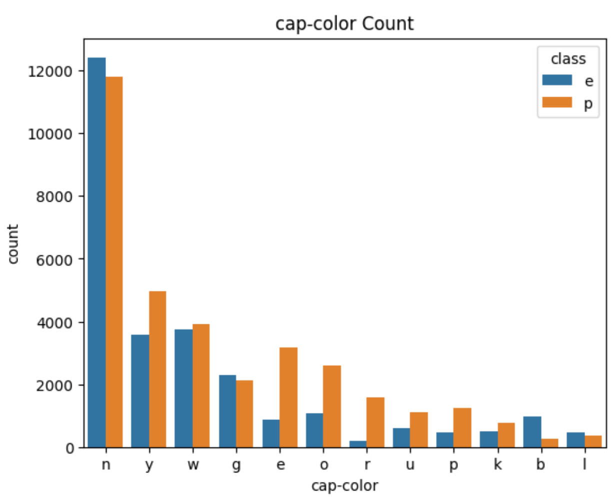

```
for f in cat_features:
    fig, axes = plt.subplots(1, 2, figsize=(14, 5))

    order = X[f].value_counts().index

    sns.countplot(x=f, hue=y_col, data=X, ax=axes[0], order=order,
hue_order=['e', 'p'])
    axes[0].set_title(f + ' Count')

    proportions = X.groupby([f,
y_col]).size().unstack().reindex(index=order)
    proportions.div(proportions.sum(axis=1), axis=0).plot(kind='bar',
stacked=True, ax=axes[1])
    axes[1].set_title(f + ' Proportions')
    axes[1].set_ylabel("Proportion")
    axes[1].set_xticklabels(axes[1].get_xticklabels(), rotation=0,
ha='right')

    plt.show()
```

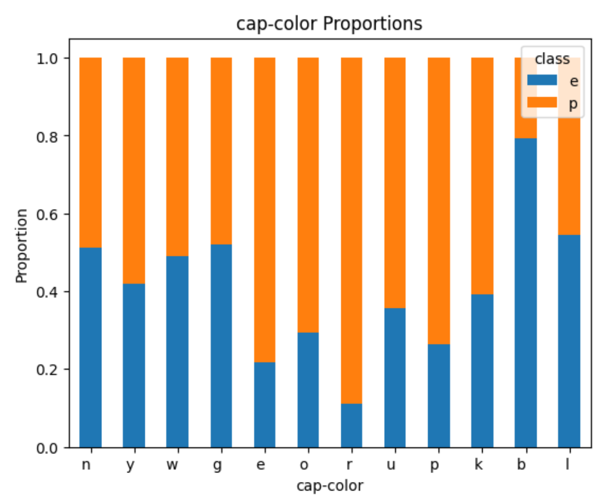

cap-shape Count
count
cap-shape
class
e
p
0
2000
4000
6000
8000
10000
12000
14000
x f s b o p c

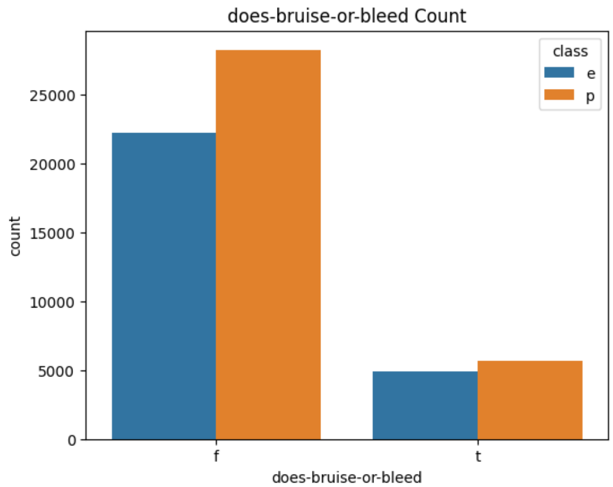

cap-shape Proportions
Proportion
cap-shape
class
e
p
0.0
0.2
0.4
0.6
0.8
1.0
x f s b o p c

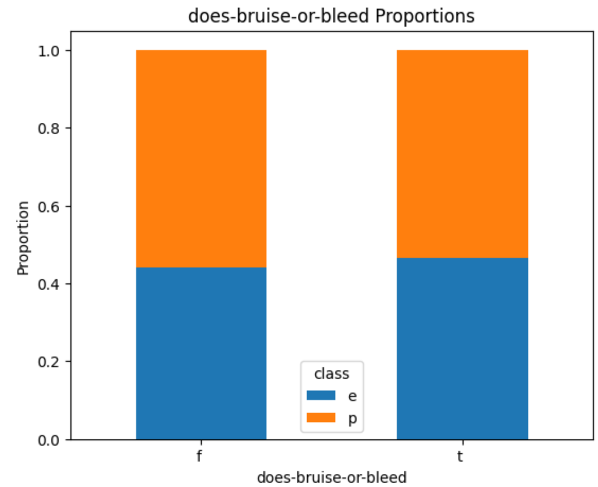

cap-surface Count
count
cap-surface
class
e
p
0
1000
2000
3000
4000
5000
6000
7000
? t s y h g d e k i w l

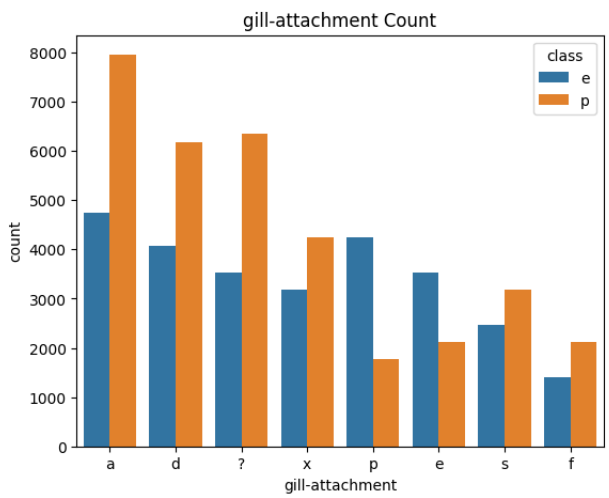

cap-surface Proportions
Proportion
cap-surface
class
e
p
0.0
0.2
0.4
0.6
0.8
1.0
? t s y h g d e k i w l

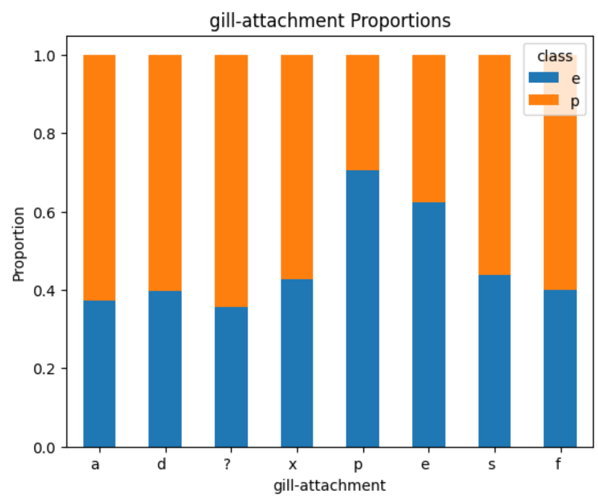

cap-color Count
count
cap-color
class
e
p
0
2000
4000
6000
8000
10000
12000
n y w g e o r u p k b l

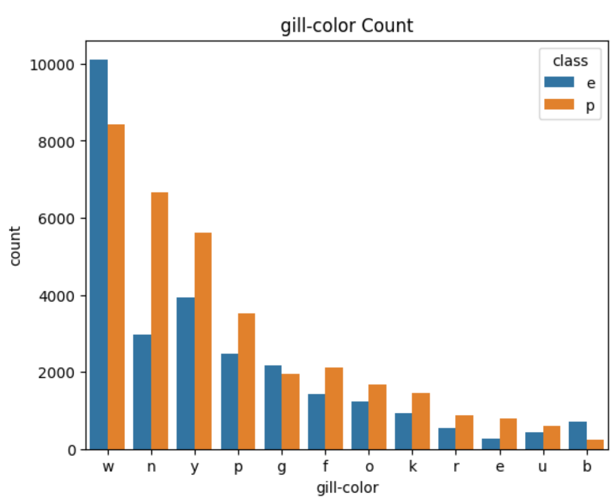

cap-color Proportions
Proportion
cap-color
class
e
p
0.0
0.2
0.4
0.6
0.8
1.0
n y w g e o r u p k b l

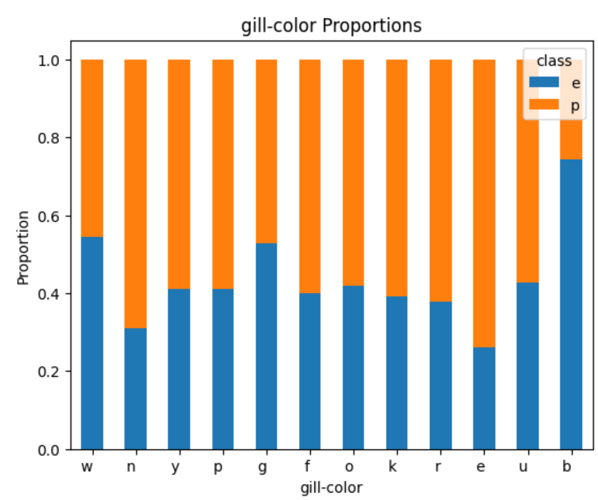

does-bruise-or-bleed Count
count
0
5000
10000
15000
20000
25000
f
t
does-bruise-or-bleed
class
e
p

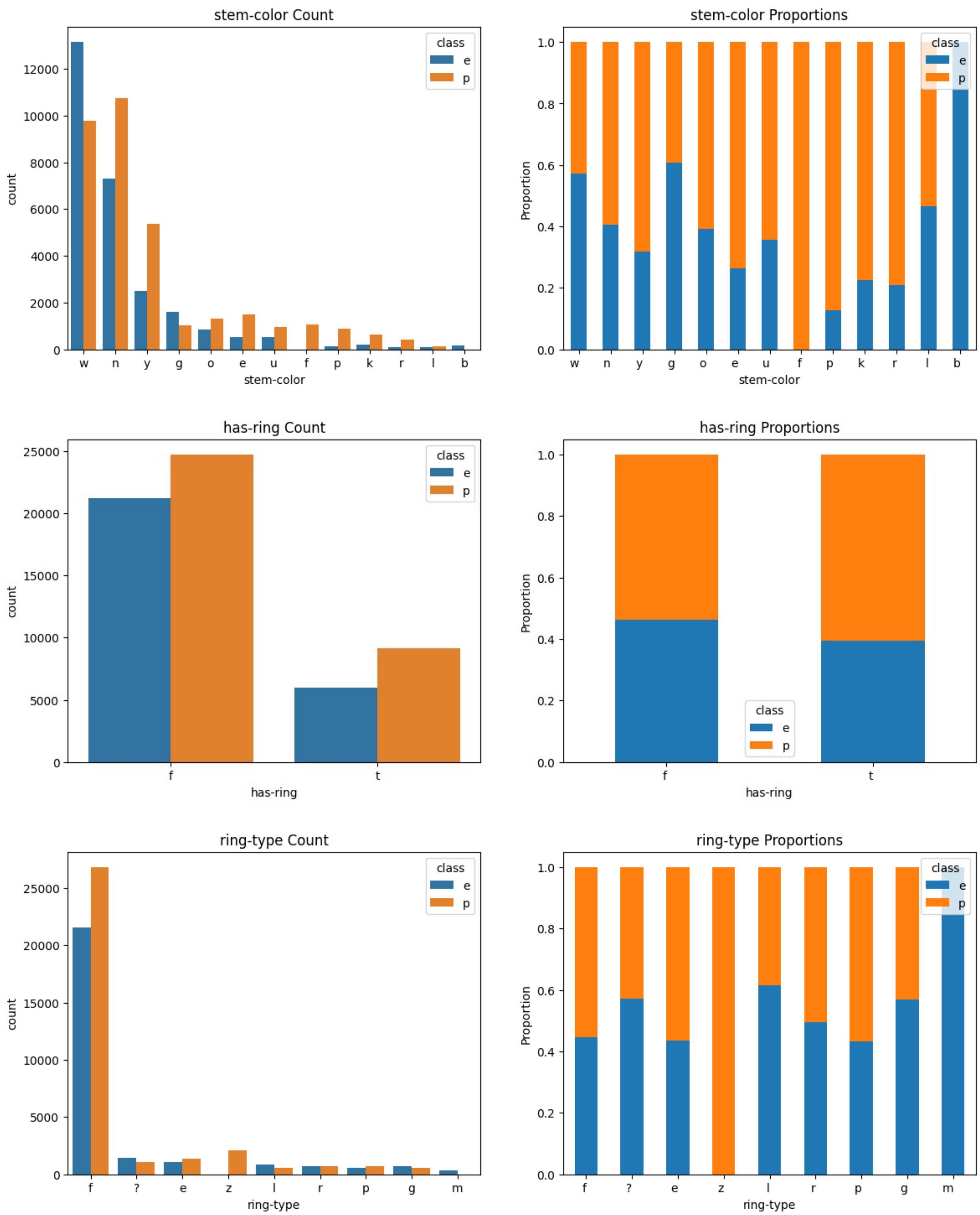

does-bruise-or-bleed Proportions
Proportion
0.0
0.2
0.4
0.6
0.8
1.0
f
t
does-bruise-or-bleed
class
e
p


gill-attachment Count
count
0
1000
2000
3000
4000
5000
6000
7000
8000
a
d
?
x
p
e
s
f
gill-attachment
class
e
p

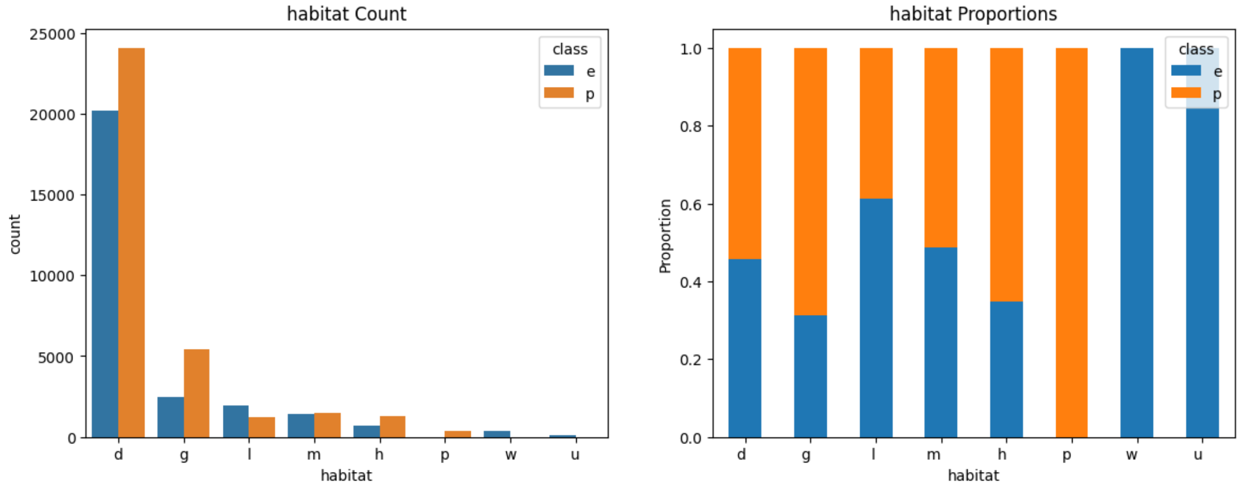

gill-attachment Proportions
Proportion
0.0
0.2
0.4
0.6
0.8
1.0
a
d
?
x
p
e
s
f
gill-attachment
class
e
p

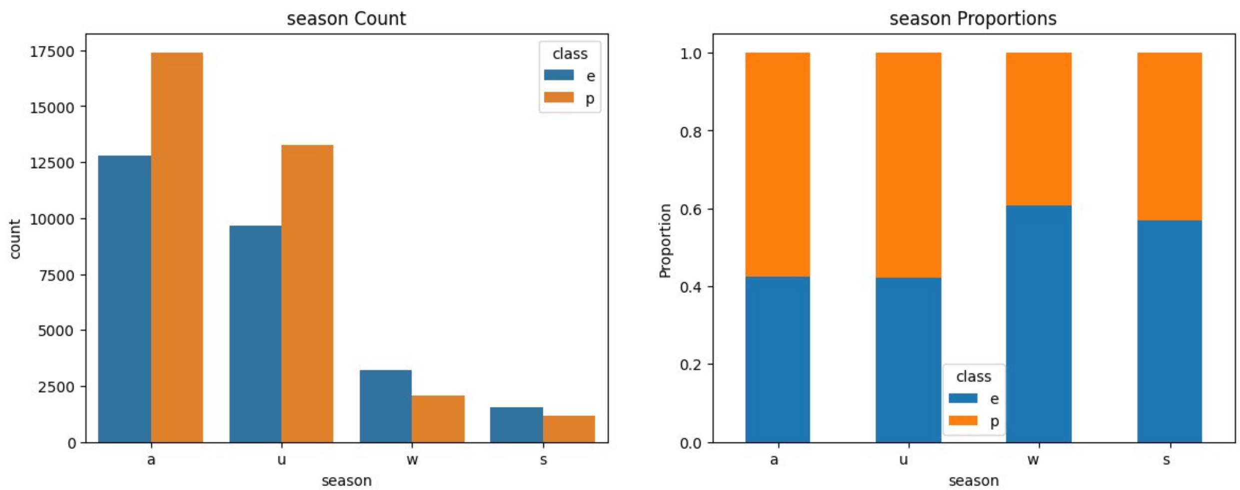

gill-color Count
count
0
2000
4000
6000
8000
10000
w
n
y
p
g
f
o
k
r
e
u
b
gill-color
class
e
p


gill-color Proportions
Proportion
0.0
0.2
0.4
0.6
0.8
1.0
w
n
y
p
g
f
o
k
r
e
u
b
gill-color
class
e
p



stem-color Count
class
e
p
count
stem-color
stem-color Proportions
Proportion
has-ring Count
has-ring
has-ring Proportions
ring-type Count
ring-type
ring-type Proportions



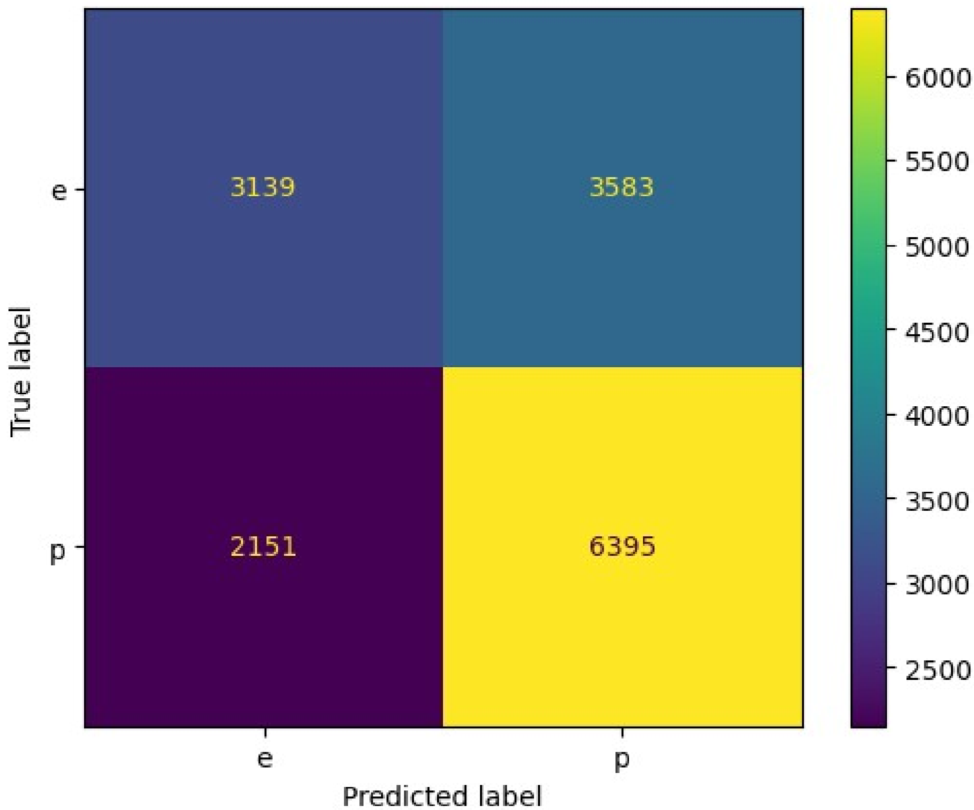



```
'''
Models

I chose several models to train and evaluate their performance and
accuracy in classifying mushrooms as edible or poisonous. I selected
Logistic Regression for its simplicity, though I anticipated it might
struggle due to the label encoding and potential multicollinearity
among the features.

I also selected Gradient Boosting and Random Forest because of their
ability to handle non-linear relationships effectively. I wanted
to compare their performance to observe the differences between these
two models. Gradient Boosting is expected to be more
computationally expensive due to its iterative nature, while Random
Forest should train relatively quickly given the small number
of features in this dataset.

Lastly, I chose a neural network (MLP Classifier) to experiment with a
supervised learning model that was not covered in class.
```

```
'''

from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import GradientBoostingClassifier,
RandomForestClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import classification_report, confusion_matrix,
ConfusionMatrixDisplay, accuracy_score
from sklearn.model_selection import train_test_split, GridSearchCV
import time

y_le, y_le_map = label_encode_data(y, {})
X_le_train, X_le_test, y_le_train, y_le_test = train_test_split(X_le,
y_le, test_size=0.25, random_state=28)

accuracy_scores = {}
def evaluate_performance(y_pred, title=None):
    if title != None:
        print(title, end='\n\n')

    disp = ConfusionMatrixDisplay(confusion_matrix(y_le_test, y_pred),
display_labels=['e', 'p'])
    disp.plot()
    plt.show()

    acc = round(accuracy_score(y_le_test, y_pred),7)
    print(f'Accuracy: {acc}', end='\n')
    if (title in training_times):
        accuracy_scores[title] = acc
        print(f'Training Time: {training_times[title]}', end='\n')


    print("\nClassification Report:")
    print(classification_report(y_le_test, y_pred))


def evaluate_features(model, title=None):
    if title != None:
        print(title, end='\n\n')

    feature_importances = pd.Series(model.feature_importances_,
index=X_le.columns)
    feature_importances =
feature_importances.sort_values(ascending=False)

    plt.figure(figsize=(10, 6))
    feature_importances.plot(kind='bar')
    plt.title("Feature Importances")
    plt.show()
```

```
def hyperparameter_tuning(model, params, X_train, y_train, cv=5):
    grid_search = GridSearchCV(
        model,
        params,
        cv=cv,
        scoring='accuracy',
        n_jobs=-1
    ).fit(X_train, y_train.iloc[:, 0])

    print(f'Best Parameters: {grid_search.best_params_}')
    return grid_search.best_estimator_

training_times = {
    # model_name: elapsed time in ms
}
def log_training_time(model_name, s, e):
    training_times[model_name] = round((e - s) * 1000)



#Logisitc Regression

s = time.perf_counter()
lr_model = LogisticRegression(n_jobs=-1).fit(X_le_train,
y_le_train.iloc[:, 0])
log_training_time('Logistic Regression', s, time.perf_counter())

lr_pred = lr_model.predict(X_le_test)
evaluate_performance(lr_pred, 'Logistic Regression')

print('Coefficients:')
print(lr_model.coef_)
```

```
Logistic Regression
```



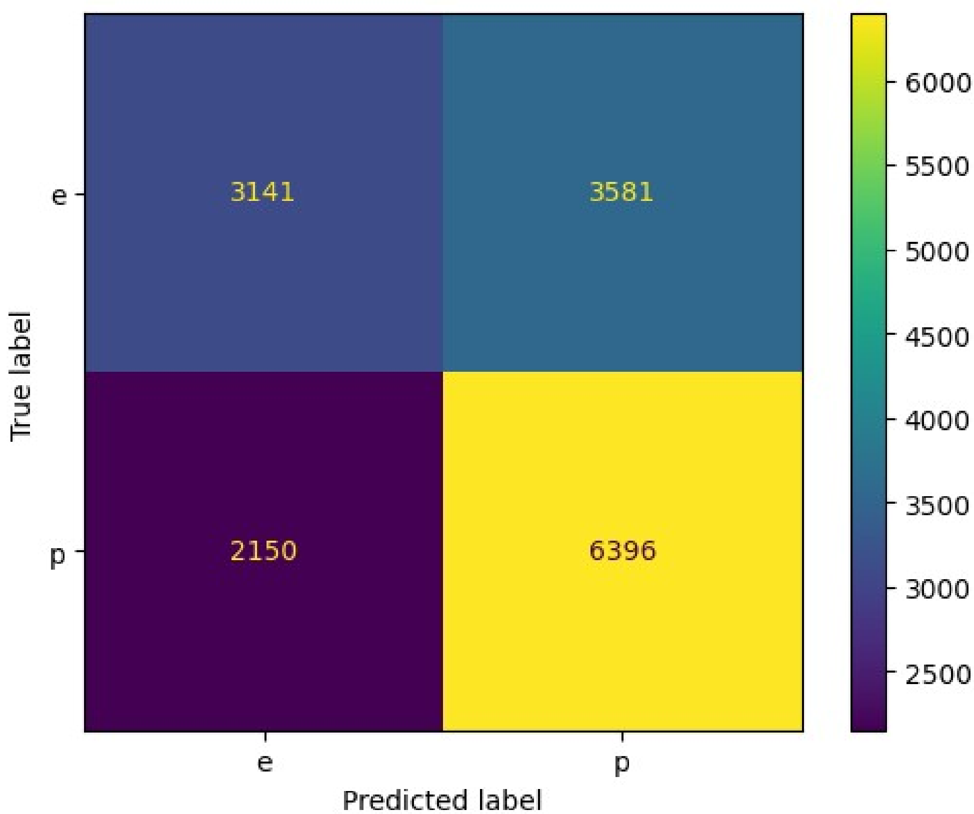

```
Accuracy: 0.6244433
Training Time: 1634

Classification Report:
              precision    recall  f1-score   support

           0       0.59      0.47      0.52      6722
           1       0.64      0.75      0.69      8546

    accuracy                           0.62     15268
   macro avg       0.62      0.61      0.61     15268
weighted avg       0.62      0.62      0.62     15268

Coefficients:
[[-0.04716796 -0.11097769  0.00660107  0.03805657  0.15151233 -
0.03516807
   0.00681629 -0.03822812 -0.01789552 -0.07154598  0.32622107
0.15393449
  -0.14328419 -0.11674118]]

lr_params = {
    'C': [0.1, 0.5, 1, 2, 5, 10],
    'class_weight': [None, {1: 2, 0: 1}],
    'solver': ['lbfgs', 'liblinear', 'newton-cg', 'newton-cholesky',
'sag', 'saga'],
```

```
    'max_iter': [100, 250, 500],
    'n_jobs': [-1]
}
tuned_lr_model = hyperparameter_tuning(
    LogisticRegression(n_jobs=-1),
    lr_params,
    X_le_train,
    y_le_train
)
```

```
Best Parameters: {'C': 5, 'class_weight': None, 'max_iter': 100,
'n_jobs': -1, 'solver': 'lbfgs'}
```

```
tuned_lr_pred = tuned_lr_model.predict(X_le_test)
evaluate_performance(tuned_lr_pred, 'Hyperparameter Tuned Logistic
Regression')

print('Coefficients:')
print(lr_model.coef_)
```

```
Hyperparameter Tuned Logistic Regression
```



```
Accuracy: 0.6246398

Classification Report:
              precision    recall  f1-score   support

           0       0.59      0.47      0.52      6722
           1       0.64      0.75      0.69      8546

    accuracy                           0.62     15268
   macro avg       0.62      0.61      0.61     15268
weighted avg       0.62      0.62      0.62     15268

Coefficients:
[[-0.04716796 -0.11097769  0.00660107  0.03805657  0.15151233 -
0.03516807
   0.00681629 -0.03822812 -0.01789552 -0.07154598  0.32622107
0.15393449
  -0.14328419 -0.11674118]]
```

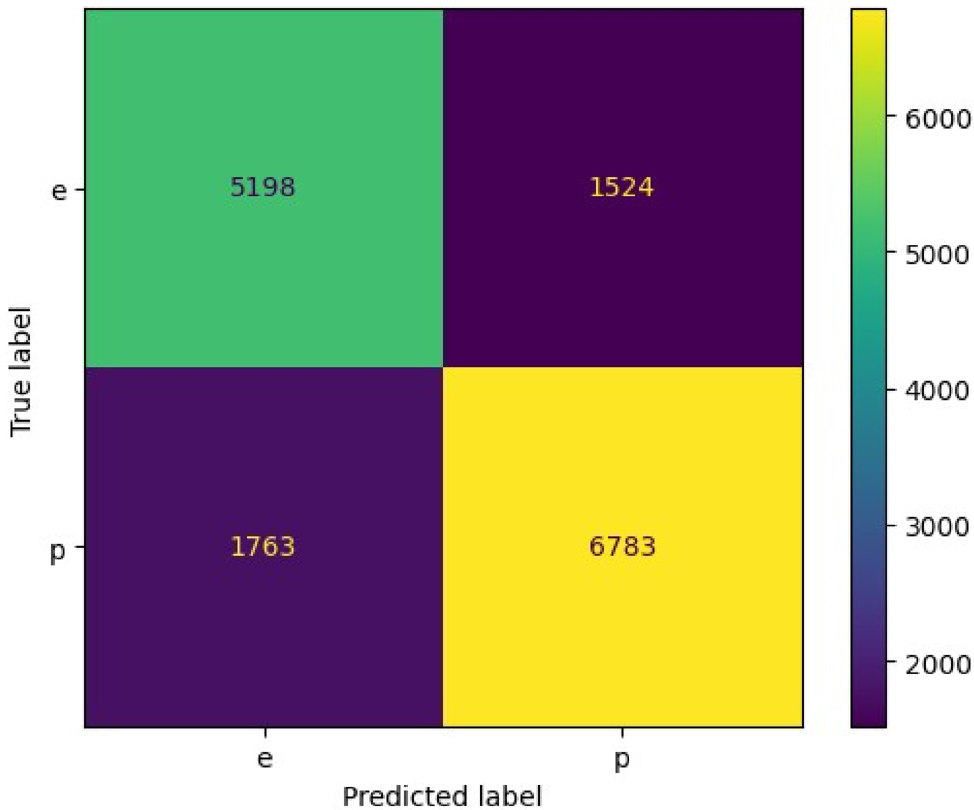
```
def one_hot_encode_data(data):
    clone = data.copy()
    oh_map = {}
    for col in clone.select_dtypes(include=['object']):
        oh_encoded = pd.get_dummies(clone[col], prefix=col)
        oh_map[col] = oh_encoded.columns.tolist()
        clone = clone.drop(columns=[col]).join(oh_encoded)
    return clone, oh_map

def oh_decode_data(data, oh_map):
    clone = data.copy()
    for original_col, oh_cols in oh_map.items():
        oh_data = clone[oh_cols]
        clone[original_col] =
oh_data.idxmax(axis=1).str[len(original_col) + 1:]  # Remove the
prefix
        clone = clone.drop(columns=oh_cols)
    return clone

X_oh, X_oh_map = one_hot_encode_data(X)
X_oh_train, X_oh_test, y_le_train, y_le_test = train_test_split(X_oh,
y_le, test_size=0.25, random_state=28)

print(X_oh.head())
```

```
   cap-diameter  stem-height  stem-width  cap-shape_b  cap-shape_c  \
0         15.26        16.95       17.09        False        False
1         16.60        17.99       18.19        False        False
2         14.07        17.80       17.74        False        False
3         14.17        15.77       15.98        False        False
4         14.64        16.53       17.20        False        False
```

```
   cap-shape_f  cap-shape_o  cap-shape_p  cap-shape_s  cap-
shape_x  ...  \
0        False        False        False        False
True  ...
1        False        False        False        False
True  ...
2        False        False        False        False
True  ...
3         True        False        False        False
False  ...
4        False        False        False        False
True  ...

   habitat_h  habitat_l  habitat_m  habitat_p  habitat_u  habitat_w
season_a  \
0      False      False      False      False      False      False
False
1      False      False      False      False      False      False
False
2      False      False      False      False      False      False
False
3      False      False      False      False      False      False
False
4      False      False      False      False      False      False
False

   season_s  season_u  season_w
0     False     False      True
1     False      True     False
2     False     False      True
3     False     False      True
4     False     False      True

[5 rows x 92 columns]
```

```
s = time.perf_counter()
lr_model = LogisticRegression(n_jobs=-1).fit(X_oh_train,
y_le_train.iloc[:, 0])
log_training_time('Logistic Regression (One-Hot)', s,
time.perf_counter())

lr_pred = lr_model.predict(X_oh_test)
evaluate_performance(lr_pred, 'Logistic Regression (One-Hot)')

print('Coefficients:')
print(lr_model.coef_)
```

```
Logistic Regression (One-Hot)
```

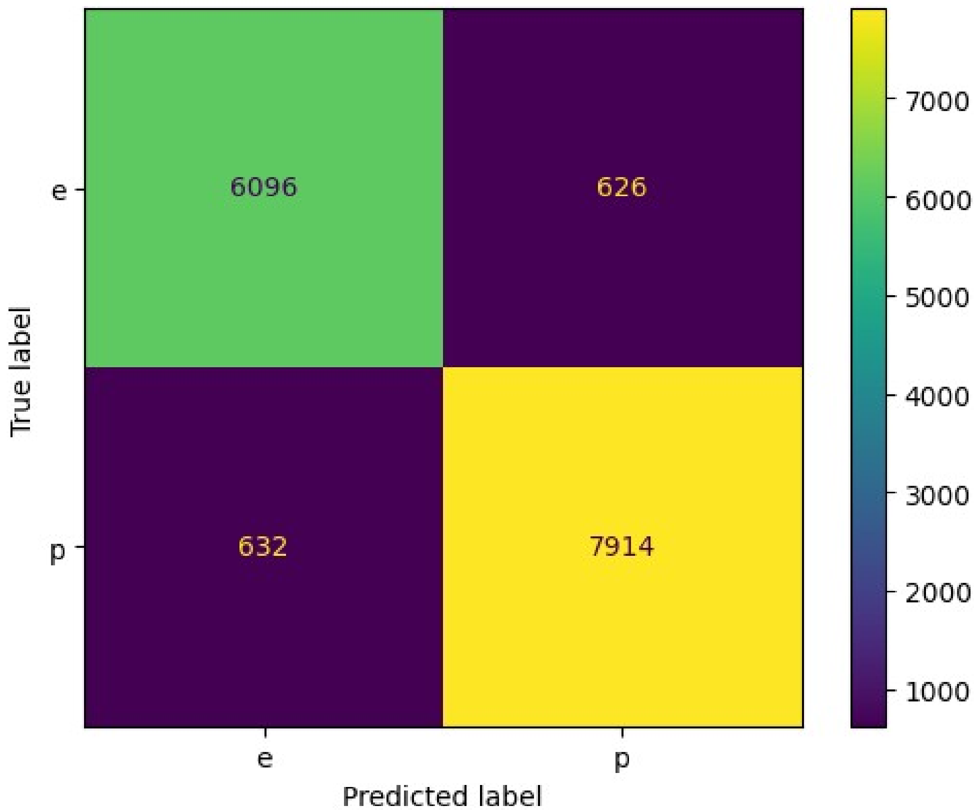



```
Accuracy: 0.7847131
Training Time: 884

Classification Report:
              precision    recall  f1-score   support

           0       0.75      0.77      0.76      6722
           1       0.82      0.79      0.80      8546

    accuracy                           0.78     15268
   macro avg       0.78      0.78      0.78     15268
weighted avg       0.79      0.78      0.79     15268

Coefficients:
[[-0.05541257  0.10342152 -0.00478196  1.10832176 -0.26035395 -
0.39931733
   0.92464971 -0.29396218 -0.76132402 -0.34600821 -0.15917259
0.01317117
   0.7765774  -0.71520952 -0.9459746   1.51887443  3.12490924 -
1.50653604
  -0.87449425 -0.04587881 -0.64723163 -0.56702903 -1.52046828
1.03537539
  -0.395653    0.55215264 -1.53578626 -0.62082615  0.68651553
0.13585475
```

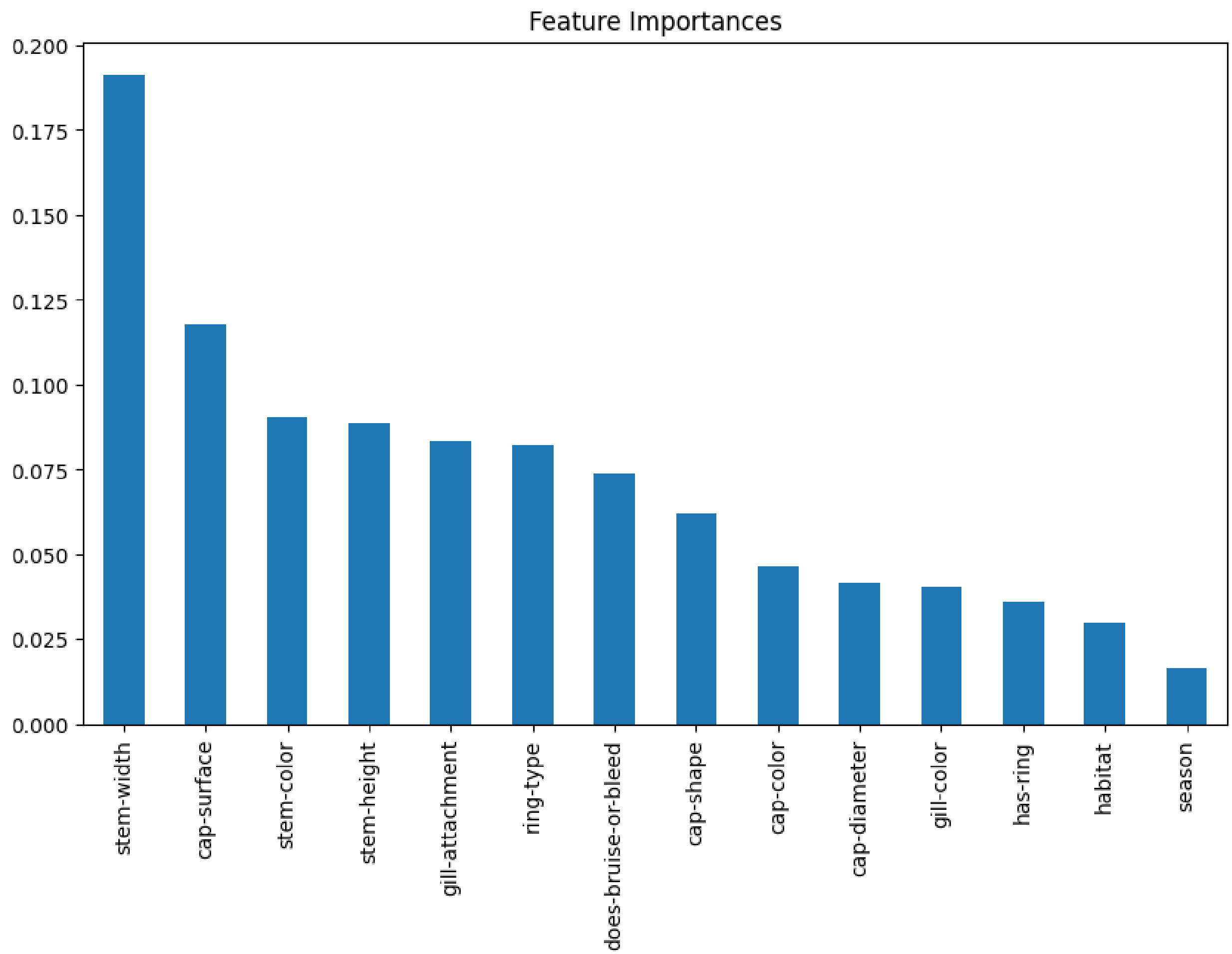
```
   1.89031149  0.42652953 -0.28953125 -0.39246861  0.03396843 -
0.06196265
   0.30403035  0.40740371  0.99547299 -0.48721207  0.06458342 -
2.22051891
   0.37093656  0.53730973 -1.84648657  1.12022589  0.06458342 -
0.19493094
   0.04525103  0.39440153 -0.09917269 -0.11557588 -0.33547314
0.23023708
  -0.09329621  0.80224225 -0.93886502  0.43531704  2.70346346 -
1.7596478
   1.93791447 -1.11989062 -0.12850012 -1.43715721  1.47208559
0.25702635
   0.14562628 -1.50569639 -0.08967026 -1.08319825  1.05520403 -
1.69514028
   0.15515206  1.3150343  -0.33383451 -0.22384495 -3.47717025
1.12876379
  -0.82492365  3.92796925  0.18297732  0.82274602  0.21037316 -
0.42634057
   0.0675442   1.55873812 -0.63849128 -1.80554118  0.61522039 -
0.80136569
   0.75841538 -0.6002643 ]]
```

```
#Gradient Boosting

s = time.perf_counter()
gb_model = GradientBoostingClassifier().fit(X_le_train,
y_le_train.iloc[:, 0])
log_training_time('Gradient Boosting', s, time.perf_counter())

gb_pred = gb_model.predict(X_le_test)
evaluate_performance(gb_pred, 'Gradient Boosting')
evaluate_features(gb_model)
```

```
Gradient Boosting
```




```
Accuracy: 0.9176054
Training Time: 4724

Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.91      0.91      6722
           1       0.93      0.93      0.93      8546

    accuracy                           0.92     15268
   macro avg       0.92      0.92      0.92     15268
weighted avg       0.92      0.92      0.92     15268
```




```
gb_params = {
    'loss': ['log_loss', 'exponential'],
    'learning_rate': [0.05, 0.1, 0.2],
    # 'n_estimators': [50, 100, 200],
    'n_estimators': [200, 300],
    # 'max_depth': [3, 5, 7],
    'max_depth': [7, 10],
    # 'min_samples_leaf': [1, 2],
    # 'max_features': ['sqrt', None],
    'max_features': ['sqrt', 'log2'],
}

X_le_train_tune, X_le_test_tune, y_le_train_tune, y_le_test_tune =
train_test_split(X_le, y_le, test_size=0.99)

hyperparameter_tuning(
    GradientBoostingClassifier(),
    gb_params,
    X_le_train_tune,
```

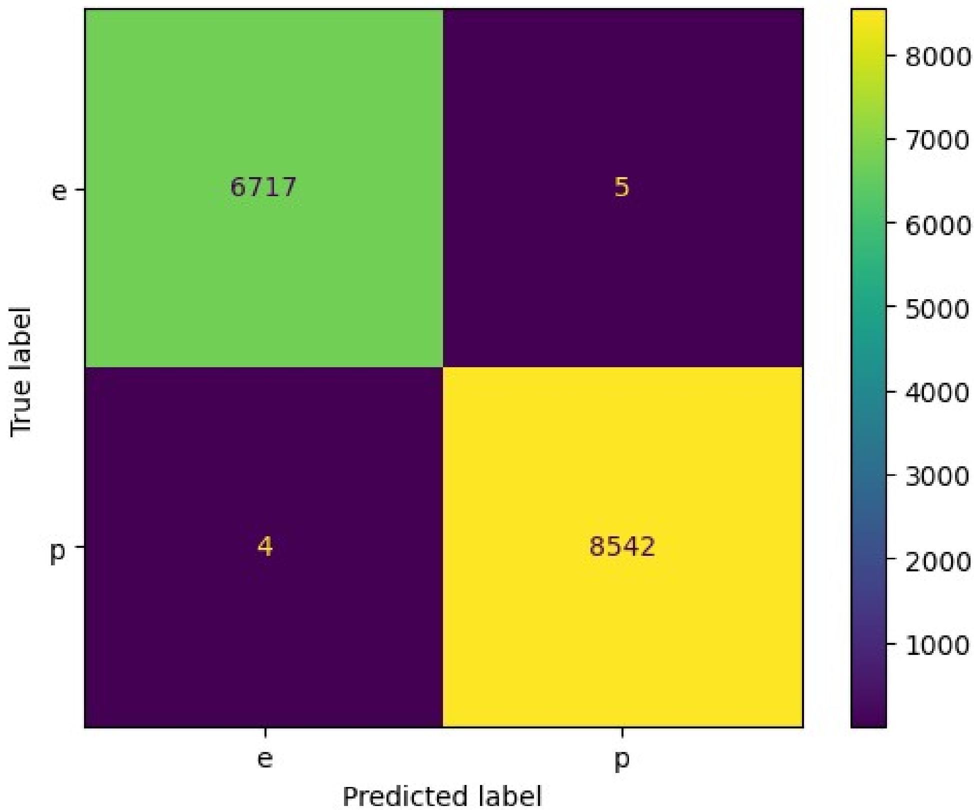
```
    y_le_train_tune
)
```

```
Best Parameters: {'learning_rate': 0.2, 'loss': 'log_loss',
'max_depth': 7, 'max_features': 'log2', 'n_estimators': 300}
```

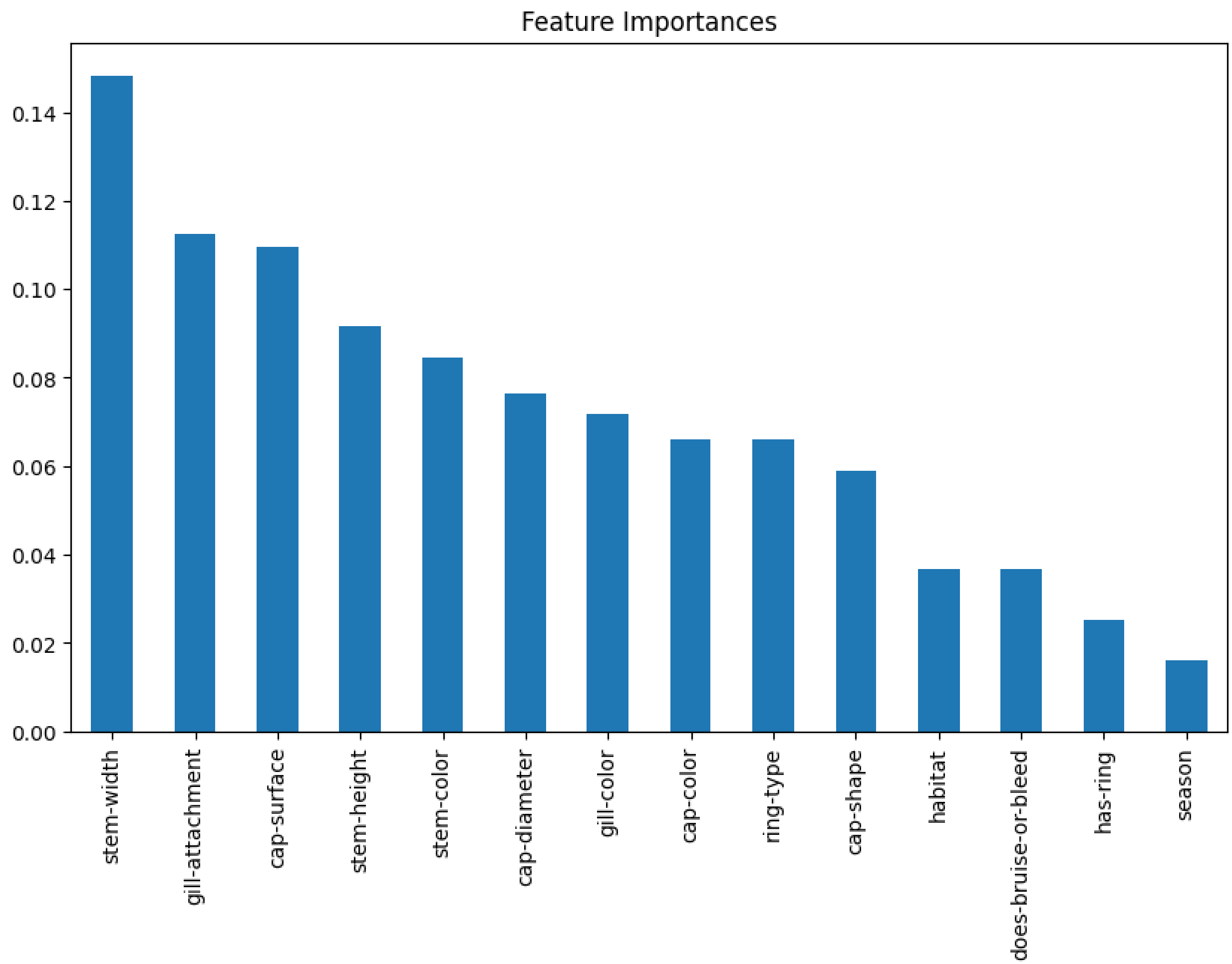
```
GradientBoostingClassifier(learning_rate=0.2, max_depth=7,
max_features='log2',
                           n_estimators=300)
```

```
'''
Best Parameters: {
    'learning_rate': 0.1,
    'loss': 'exponential',
    'max_depth': 7,
    'max_features': 'sqrt',
    'min_samples_leaf': 1,
    'n_estimators': 200
}
'''

s = time.perf_counter()
tuned_gb_model_1 = GradientBoostingClassifier(
    learning_rate=0.1,
    loss='exponential',
    max_depth=7,
    max_features='sqrt',
    min_samples_leaf=1,
    n_estimators=200
).fit(X_le_train, y_le_train.iloc[:, 0])
log_training_time('Gradient Boosting (Hyperparameter Tuned)', s,
time.perf_counter())

tuned_gb_pred = tuned_gb_model_1.predict(X_le_test)
evaluate_performance(tuned_gb_pred, 'Gradient Boosting (Hyperparameter
Tuned)')
evaluate_features(tuned_gb_model_1)
```

```
Gradient Boosting (Hyperparameter Tuned)
```



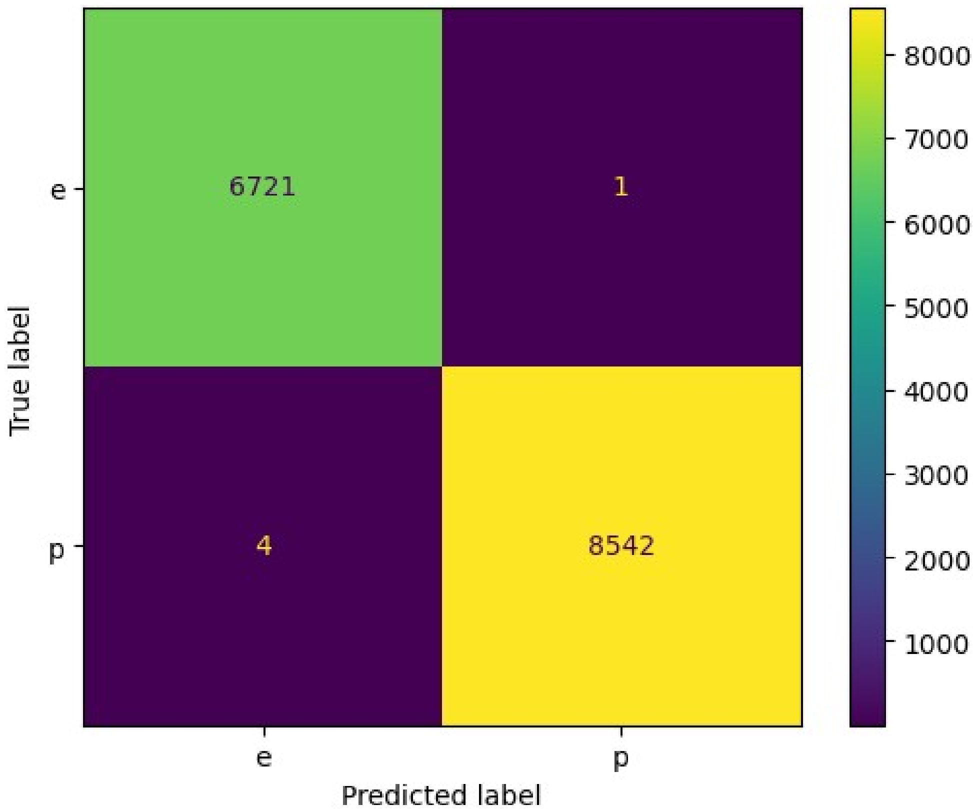

```
Accuracy: 0.9994105
Training Time: 12281

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      6722
           1       1.00      1.00      1.00      8546

    accuracy                           1.00     15268
   macro avg       1.00      1.00      1.00     15268
weighted avg       1.00      1.00      1.00     15268
```



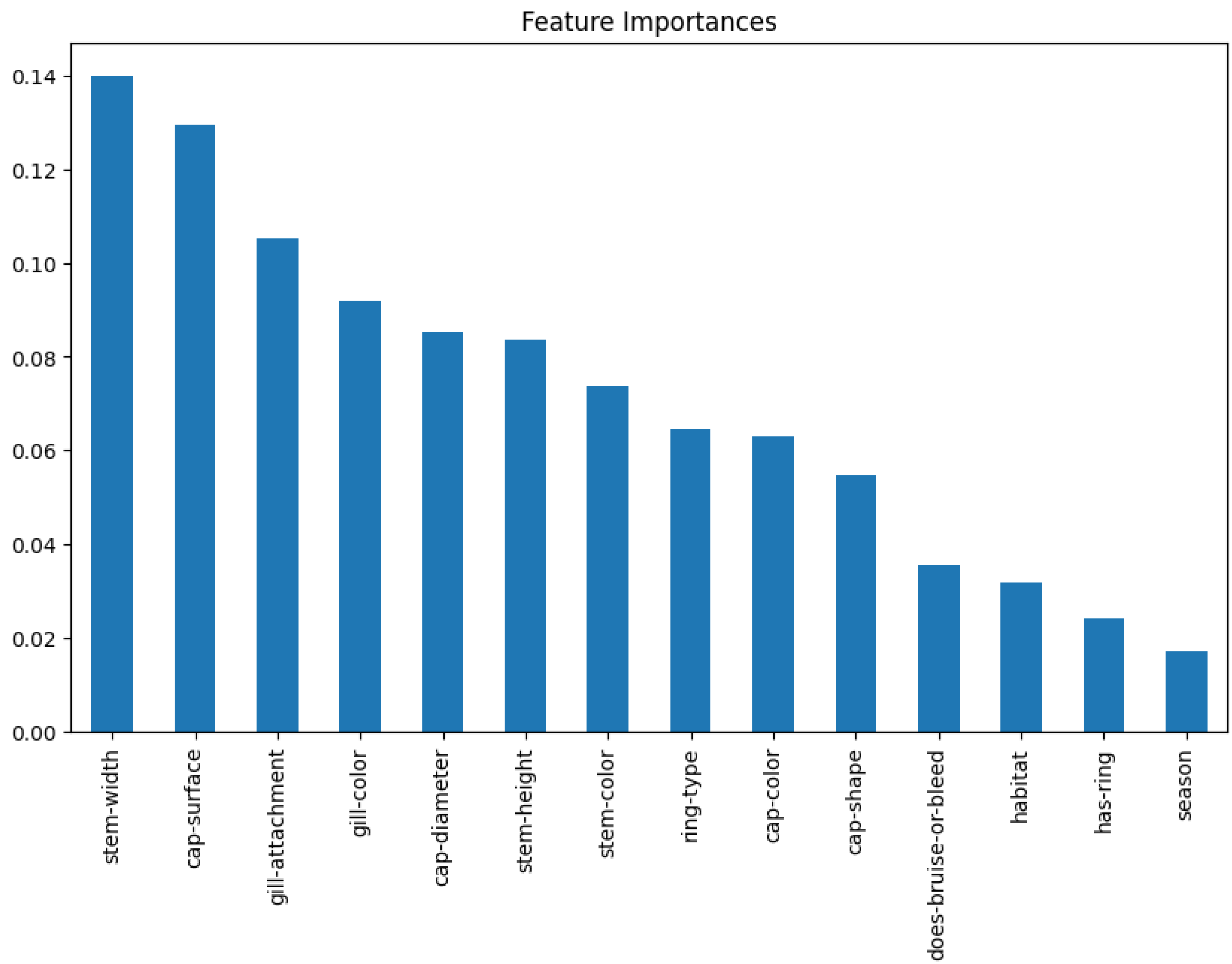

```
'''
Best Parameters: {
    'learning_rate': 0.2,
    'loss': 'log_loss',
    'max_depth': 7,
    'max_features': 'sqrt',
    'min_samples_leaf': 1,
    'n_estimators': 200
}
'''

tuned_gb_model_2 = GradientBoostingClassifier(
    learning_rate=0.2,
    loss='log_loss',
    max_depth=7,
    max_features='sqrt',
    min_samples_leaf=1,
    n_estimators=200
).fit(X_le_train, y_le_train.iloc[:, 0])
tuned_gb_pred = tuned_gb_model_2.predict(X_le_test)
```

```
evaluate_performance(tuned_gb_pred, 'Gradient Boosting (Hyperparameter Tuned) (2)')
evaluate_features(tuned_gb_model_2)
```

```
Hyparameter Tuned Gradient Boosting Classifier (2)
```

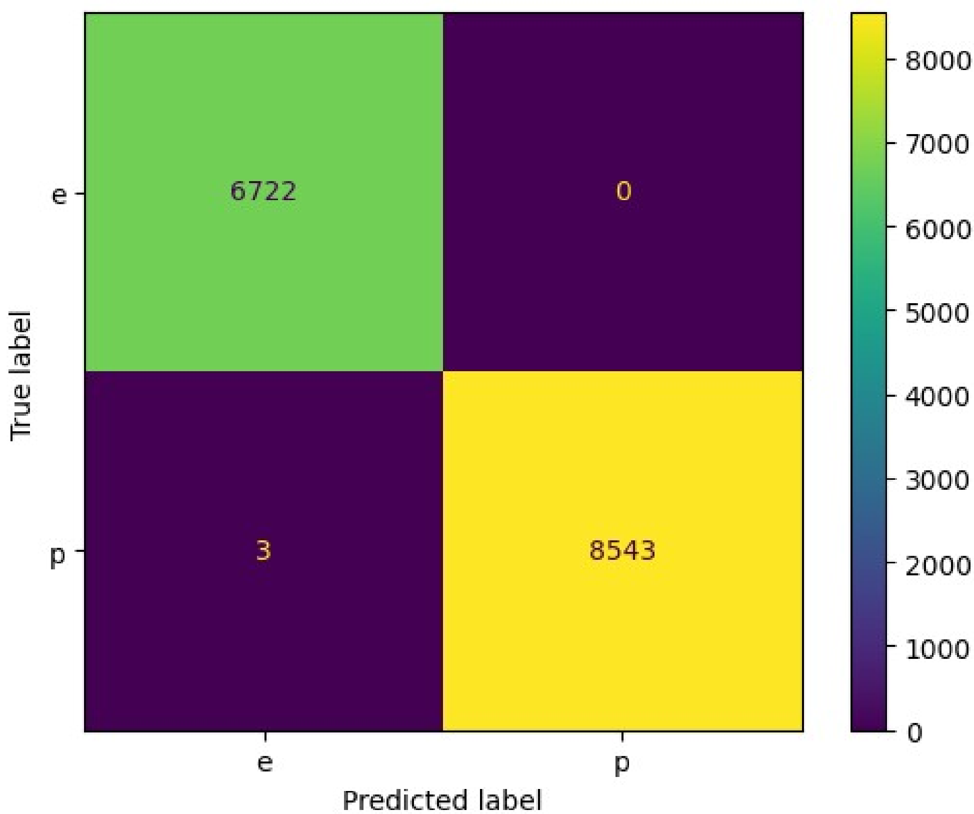



```
Accuracy: 0.9996725176840451

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      6722
           1       1.00      1.00      1.00      8546

    accuracy                           1.00     15268
   macro avg       1.00      1.00      1.00     15268
weighted avg       1.00      1.00      1.00     15268
```

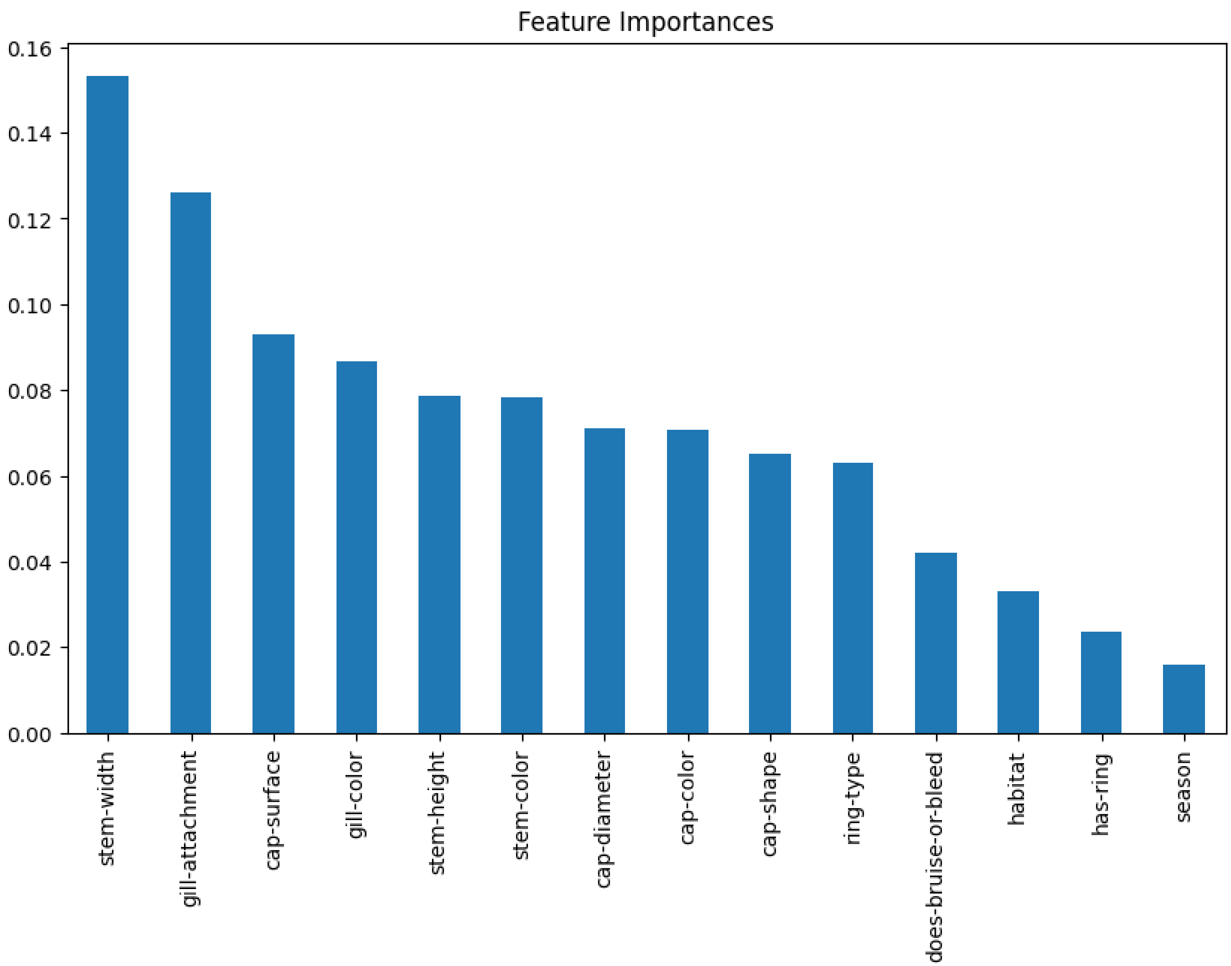



```
'''
Best Parameters: {
    'learning_rate': 0.1,
    'loss': 'exponential',
    'max_depth': 10,
    'max_features': 'log2',
    'n_estimators': 300
}
'''

tuned_gb_model_3 = GradientBoostingClassifier(
    learning_rate=0.1,
    loss='exponential',
    max_depth=10,
    max_features='log2',
    min_samples_leaf=1,
    n_estimators=300
).fit(X_le_train, y_le_train.iloc[:, 0])
tuned_gb_pred = tuned_gb_model_3.predict(X_le_test)
evaluate_performance(tuned_gb_pred, 'Gradient Boosting (Hyperparameter
```

```
Tuned) (3)')
evaluate_features(tuned_gb_model_3)

Hyparameter Tuned Gradient Boosting Classifier (3)
```

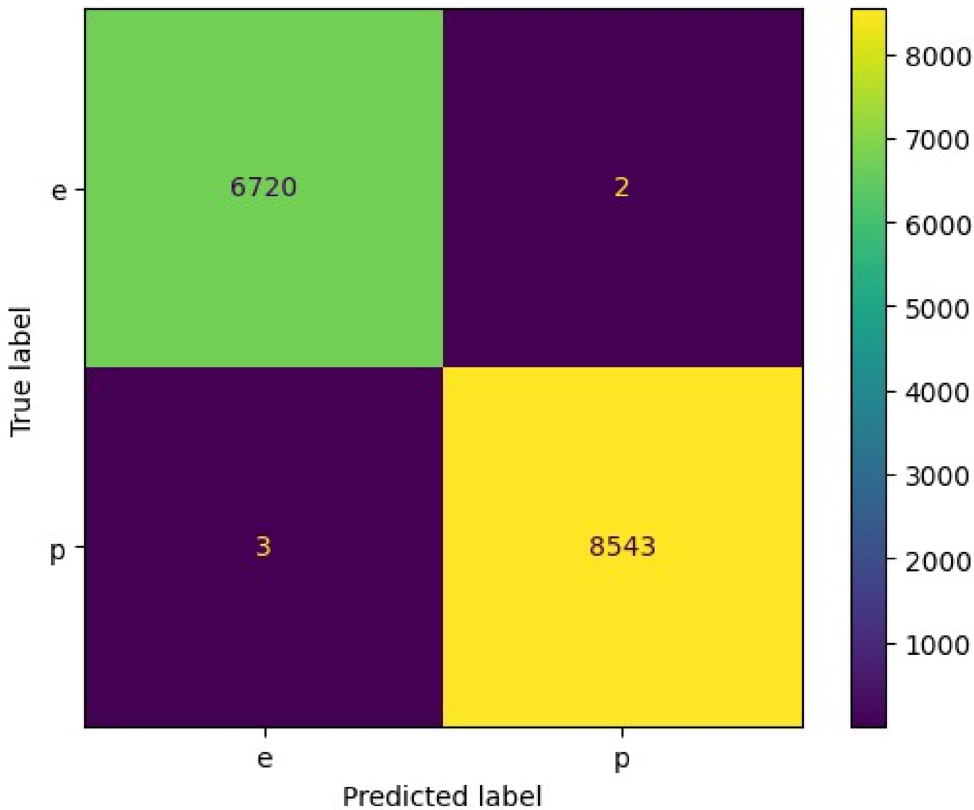



```
Accuracy: 0.999803510610427

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      6722
           1       1.00      1.00      1.00      8546

    accuracy                           1.00     15268
   macro avg       1.00      1.00      1.00     15268
weighted avg       1.00      1.00      1.00     15268
```

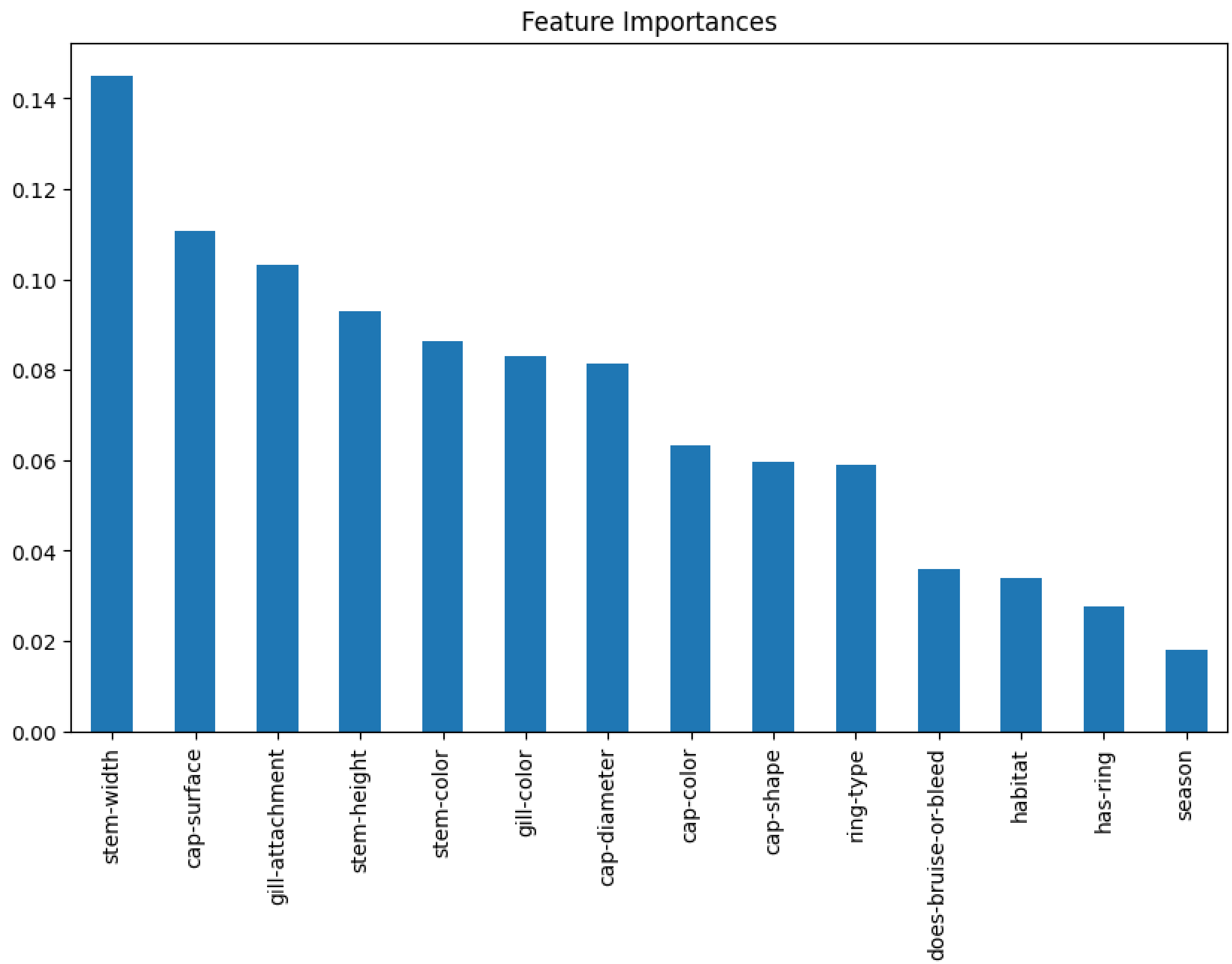



```
#Random Forest

s = time.perf_counter()
rf_model = RandomForestClassifier(n_jobs=-1).fit(X_le_train,
y_le_train.iloc[:, 0])
log_training_time('Random Forest', s, time.perf_counter())

rf_pred = rf_model.predict(X_le_test)
evaluate_performance(rf_pred, 'Random Forest')
evaluate_features(rf_model)
```

```
Random Forest
```

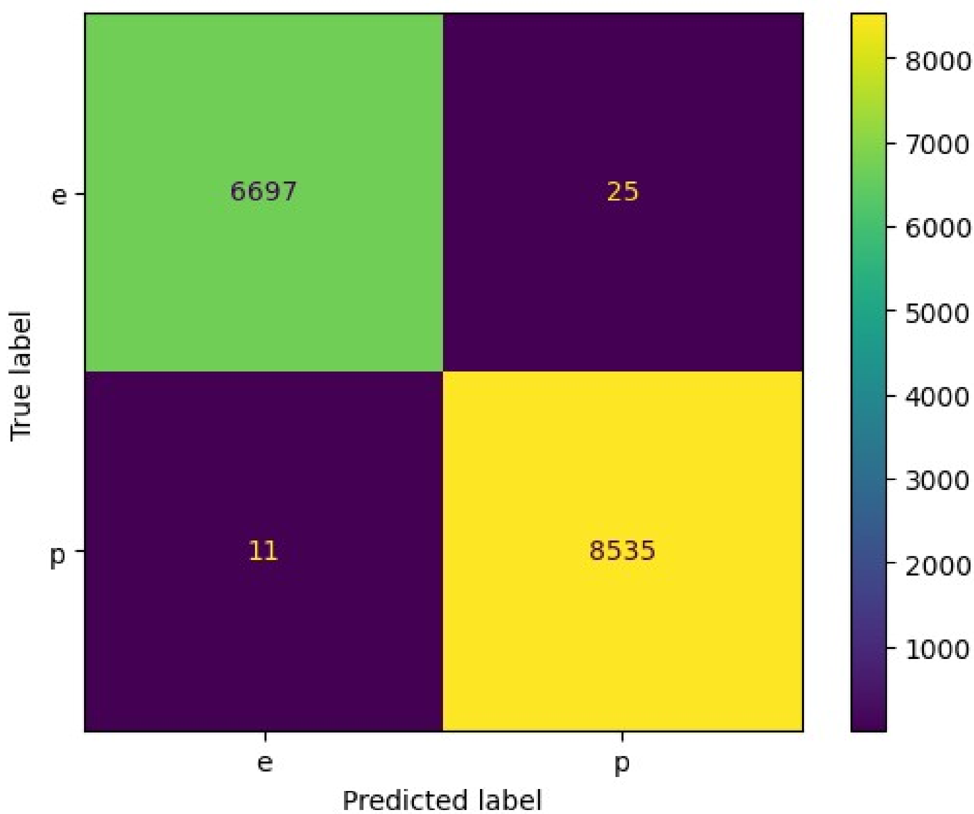



```
Accuracy: 0.9996725
Training Time: 778

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      6722
           1       1.00      1.00      1.00      8546

    accuracy                           1.00     15268
   macro avg       1.00      1.00      1.00     15268
weighted avg       1.00      1.00      1.00     15268
```



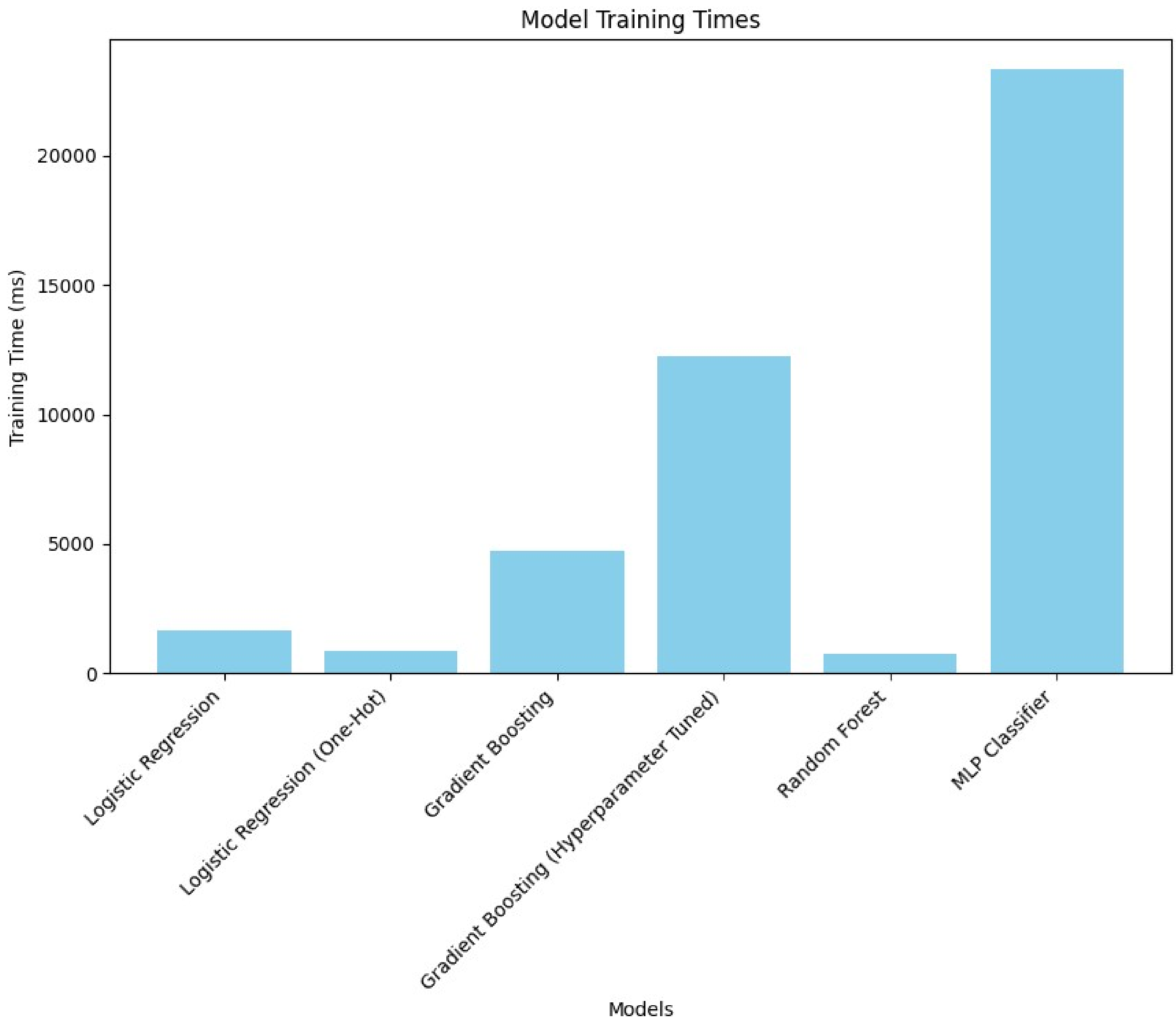

```
#MLPClassifier (Neural Network)
# (not covered in class)

s = time.perf_counter()
mlp_model = MLPClassifier().fit(X_le_train, y_le_train.iloc[:, 0])
log_training_time('MLP Classifier', s, time.perf_counter())

mlp_pred = mlp_model.predict(X_le_test)
evaluate_performance(mlp_pred, 'MLP Classifier')
```

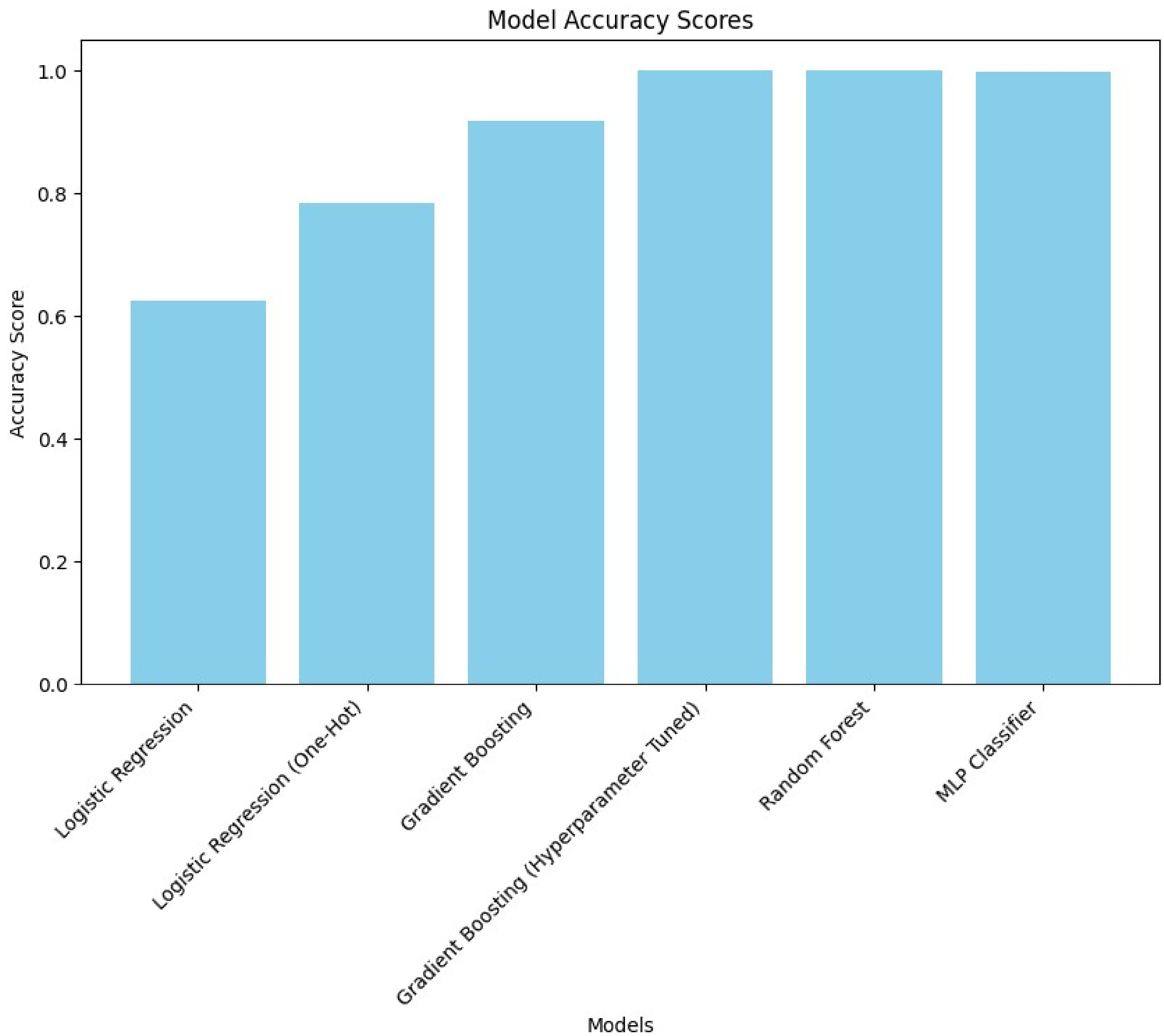
```
MLP Classifier
```




```
Accuracy: 0.9976421
Training Time: 23316

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      6722
           1       1.00      1.00      1.00      8546

    accuracy                           1.00     15268
   macro avg       1.00      1.00      1.00     15268
weighted avg       1.00      1.00      1.00     15268


'''
Results and Analysis

For the task of classifying mushrooms as edible versus poisonous, the
consequences of labeling a poisonous mushroom as edible are
potentially deadly. Therefore, a high precision score is crucial for
minimizing false positives, i.e., labeling a poisonous mushroom as
edible. Mislabeling edible mushrooms as poisonous is not nearly as
consequential. However, for the sake of developing a good model, I
aimed to achieve a high recall score as well, and ultimately a high
F1-score since it is derived from both precision and recall.
```

```python
Generally, the models performed with such high precision, recall, and
F1-scores that there wasn't enough granularity to distinguish
between them meaningfully. For my model comparisons, I plotted two
graphs: one showing the accuracy scores and the other illustrating
the training times of the models.

Three models attained near-perfect accuracy scores: the
hyperparameter-tuned gradient boosting classifier, the random forest
classifier,
and the MLP classifier. However, the random forest classifier was
exceptionally faster to train and did not require any advanced
training techniques to achieve such a high accuracy score.

'''
None #Disable cell output

models = list(training_times.keys())
times = list(training_times.values())

plt.figure(figsize=(10, 6))
plt.bar(models, times, color='skyblue')
plt.xlabel("Models")
plt.ylabel("Training Time (ms)")
plt.title("Model Training Times")
plt.xticks(rotation=45, ha="right")
plt.show()

models = list(accuracy_scores.keys())
times = list(accuracy_scores.values())

plt.figure(figsize=(10, 6))
plt.bar(models, times, color='skyblue')
plt.xlabel("Models")
plt.ylabel("Accuracy Score")
plt.title("Model Accuracy Scores")
plt.xticks(rotation=45, ha="right")
plt.show()
```


Model Training Times
Training Time (ms)
0
5000
10000
15000
20000
Logistic Regression
Logistic Regression (One-Hot)
Gradient Boosting
Gradient Boosting (Hyperparameter Tuned)
Random Forest
MLP Classifier
Models


Model Accuracy Scores
Accuracy Score
1.0
0.8
0.6
0.4
0.2
0.0
Logistic Regression
Logistic Regression (One-Hot)
Gradient Boosting
Gradient Boosting (Hyperparameter Tuned)
Random Forest
MLP Classifier
Models