ML Lab

Assignment 1:

Machine Learning Classification on Iris and Breast Cancer Datasets:

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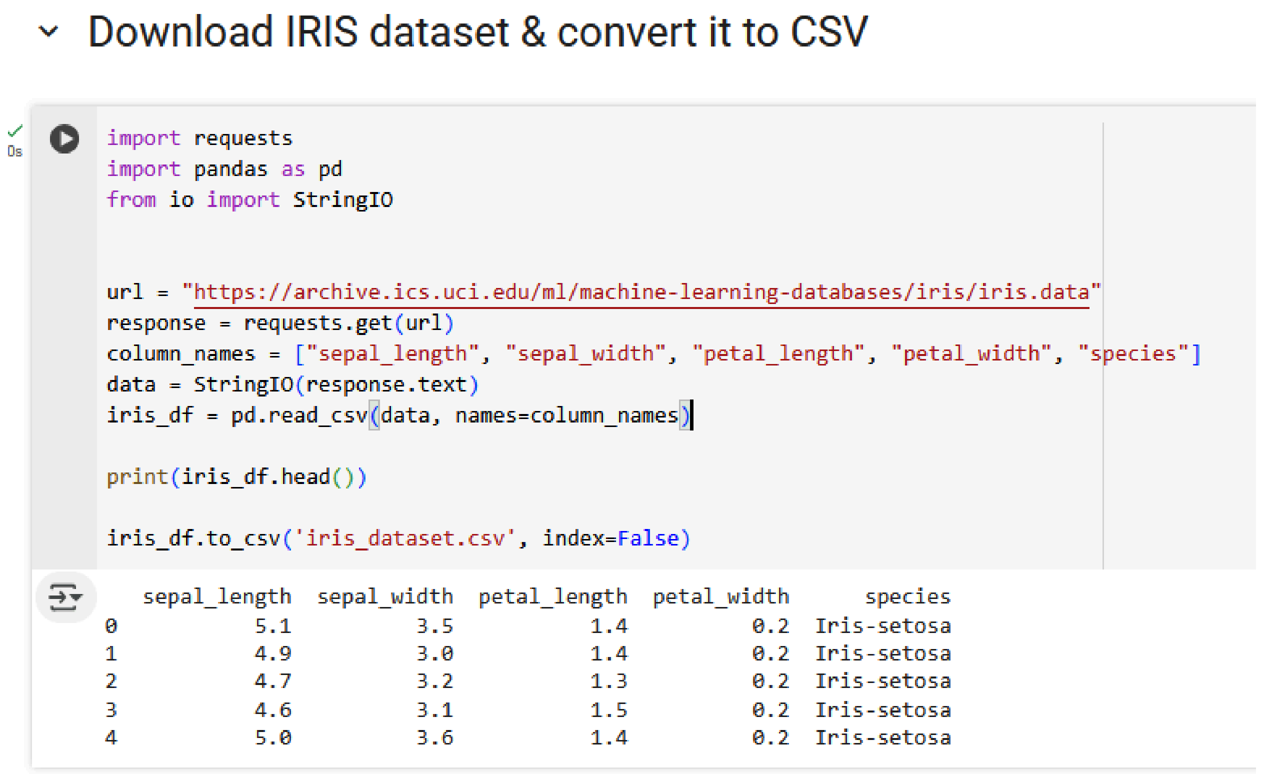
Github Link:
https://github.com/abhijitdas6371/ML_LAB/blob/main/Ass1/Assignment1_ML_Lab.ipynb

1. Problem Statement

The goal is to build and evaluate classification models on two datasets: the Iris dataset and the Breast Cancer dataset. The task is to accurately predict the class labels of samples based on their feature values.

a. Iris dataset: Predict the species (setosa, versicolor, virginica) from measurements of flower attributes.
b. Breast Cancer dataset: Predict the diagnosis (malignant or benign) based on tumor features extracted from digitized images.

2. Iris Dataset Download and CSV Conversion Script



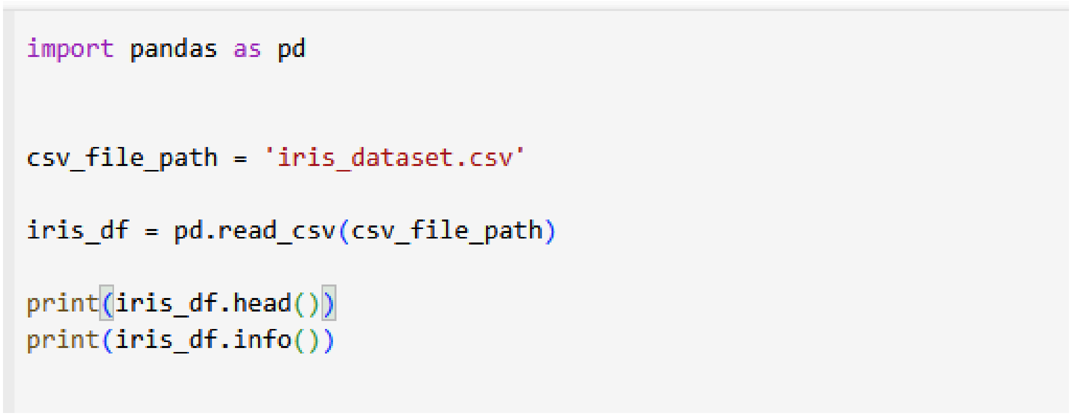
Download IRIS dataset & convert it to CSV

```
import requests
import pandas as pd
from io import StringIO


url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"
response = requests.get(url)
column_names = ["sepal_length", "sepal_width", "petal_length", "petal_width", "species"]
data = StringIO(response.text)
iris_df = pd.read_csv(data, names=column_names)

print(iris_df.head())

iris_df.to_csv('iris_dataset.csv', index=False)
```

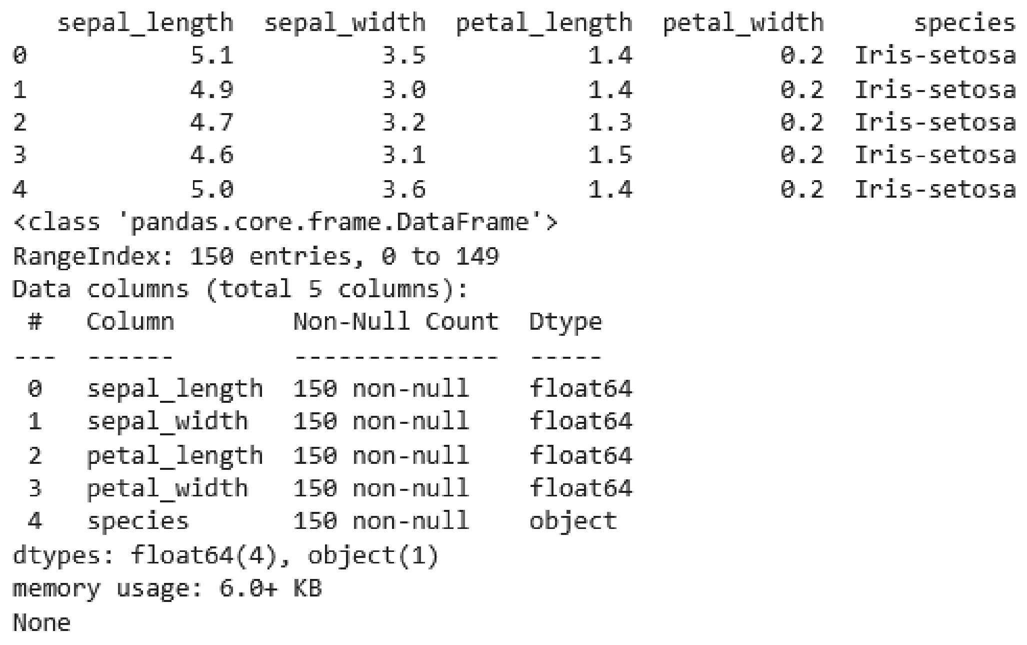
```
   sepal_length  sepal_width  petal_length  petal_width      species
0           5.1          3.5           1.4          0.2  Iris-setosa
1           4.9          3.0           1.4          0.2  Iris-setosa
2           4.7          3.2           1.3          0.2  Iris-setosa
3           4.6          3.1           1.5          0.2  Iris-setosa
4           5.0          3.6           1.4          0.2  Iris-setosa
```

Script Overview
Download data: The raw Iris dataset is fetched via HTTP from the UCI repository.
Load into DataFrame: The downloaded data is parsed into a structured pandas DataFrame with meaningful column headers.
Save to CSV: The DataFrame is saved locally as iris_dataset.csv, facilitating easy loading in future workflows without requiring repeated downloads.

3. **Load and Inspect Iris Dataset from CSV**



```python
import pandas as pd


csv_file_path = 'iris_dataset.csv'

iris_df = pd.read_csv(csv_file_path)

print(iris_df.head())
print(iris_df.info())
```

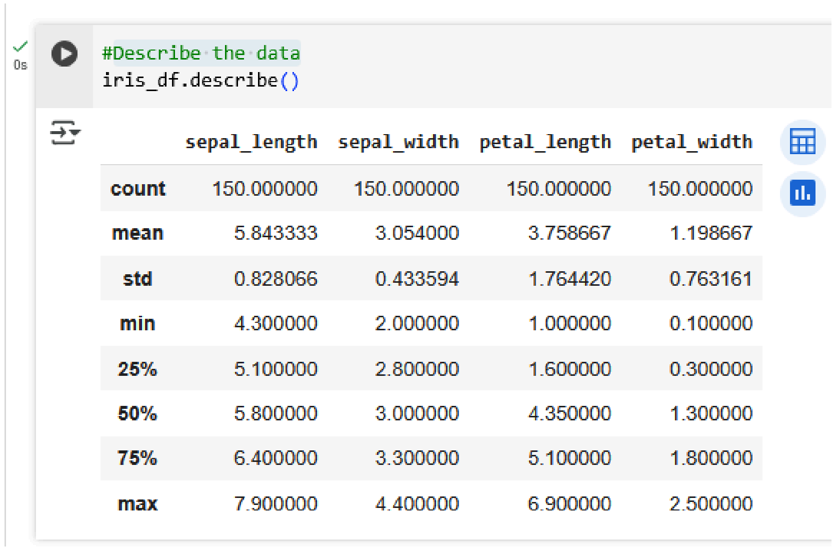


```
   sepal_length  sepal_width  petal_length  petal_width      species
0           5.1          3.5           1.4          0.2  Iris-setosa
1           4.9          3.0           1.4          0.2  Iris-setosa
2           4.7          3.2           1.3          0.2  Iris-setosa
3           4.6          3.1           1.5          0.2  Iris-setosa
4           5.0          3.6           1.4          0.2  Iris-setosa
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 non-null    float64
 3   petal_width   150 non-null    float64
 4   species       150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
None
```

pd.read_csv: Load the CSV file into a pandas DataFrame
head(): Shows the first five rows of the dataset, allowing you to quickly verify the contents.

info(): Provides details about each column, including data types and counts of non-null values, useful for identifying missing data and understanding the dataset structure.

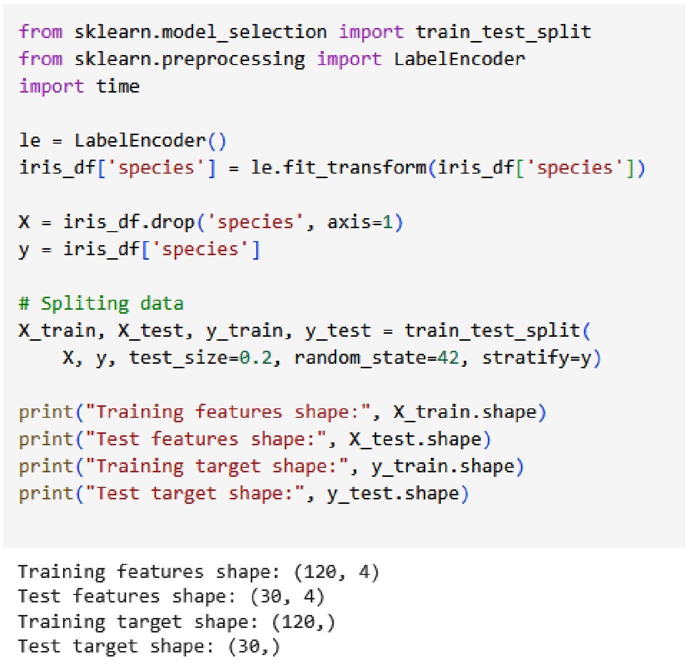
4. Describe the data



```
#Describe the data
iris_df.describe()
```

	sepal_length	sepal_width	petal_length	petal_width
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.054000	3.758667	1.198667
std	0.828066	0.433594	1.764420	0.763161
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

5. Iris Dataset Preprocessing and Train-Test Split



```python
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
import time

le = LabelEncoder()
iris_df['species'] = le.fit_transform(iris_df['species'])

X = iris_df.drop('species', axis=1)
y = iris_df['species']

# Spliting data
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y)

print("Training features shape:", X_train.shape)
print("Test features shape:", X_test.shape)
print("Training target shape:", y_train.shape)
print("Test target shape:", y_test.shape)
```

```
Training features shape: (120, 4)
Test features shape: (30, 4)
Training target shape: (120,)
Test target shape: (30,)
```

Label Encoding:

Converts categorical species names to numeric labels
(setosa → 0, versicolor → 1, virginica → 2) for model compatibility..

Train-Test Split: Divides the dataset into 80% training data and 20% test data, ensuring the model is evaluated on unseen data.

6. Importing the model(Decision Tree), training, testing, printing accuracy parameters

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score,  classification_report
from sklearn.preprocessing import StandardScaler
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt
import time
import plotly.express as px
from sklearn.model_selection import GridSearch
```

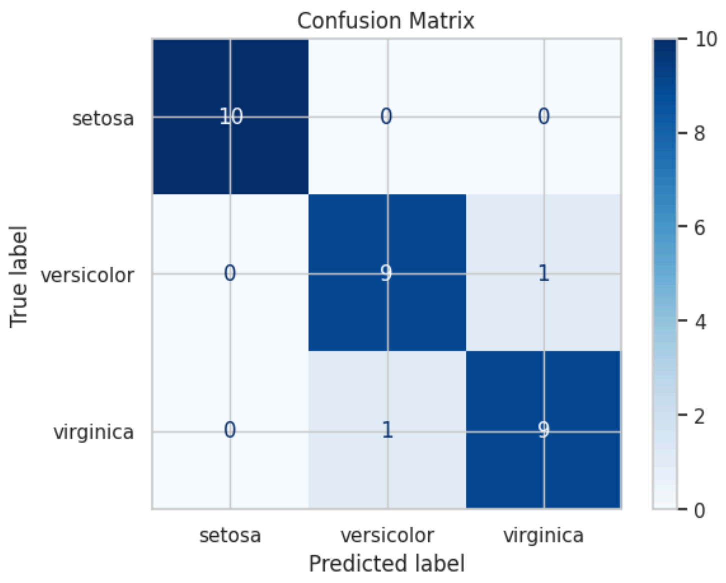
7. Training, Testing and Parameter Tuning to choose the best model

```
# Define the parameter grid
param_grid = {
    'max_depth': [3, 5, 7, 10],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'criterion': ['gini', 'entropy'],
    'max_features': ['sqrt', 'log2', None]
}
# Create a base DecisionTreeClassifier
dt_base = DecisionTreeClassifier(random_state=42)
# Set up GridSearchCV
grid_search = GridSearchCV(estimator=dt_base,
                           param_grid=param_grid,
                           scoring='accuracy',
                           cv=5,
                           n_jobs=-1,  # Use all processors
                           verbose=1)
# Start timing
start_time = time.time()
# Fit GridSearchCV
grid_search.fit(X_train, y_train)
# End timing
end_time = time.time()
time_taken = (end_time - start_time) * 1000  # in ms
# Get best model from grid search
best_dt = grid_search.best_estimator_
# Predict using the best model (Test set)
y_pred_test = best_dt.predict(X_test)
# Evaluate the model (Test)
test_accuracy = accuracy_score(y_test, y_pred_test)
```

```
# Evaluate the model (Train)
class_report = classification_report(y_test, y_pred_test)

# Print results
print(f"Best Parameters: {grid_search.best_params_}")
print(f"Test Set Accuracy: {test_accuracy * 100:.2f}%")
from sklearn.metrics import ConfusionMatrixDisplay
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test,
display_labels=['setosa', 'versicolor', 'virginica'],
                                        cmap='Blues')
plt.title(f'Confusion Matrix')
plt.show()
print("\nClassification Report (Test):")
print(class_report)
n tree
plt.figure(figsize=(12, 8))
plot_tree(best_dt,
          filled=True,
          feature_names=X.columns,
          class_names=['setosa', 'versicolor', 'virginica'],
          rounded=True)
plt.title("Best Decision Tree Visualization")
plt.show()
print(f"\nTime taken for training and tuning: {time_taken:.4f} ms")
```

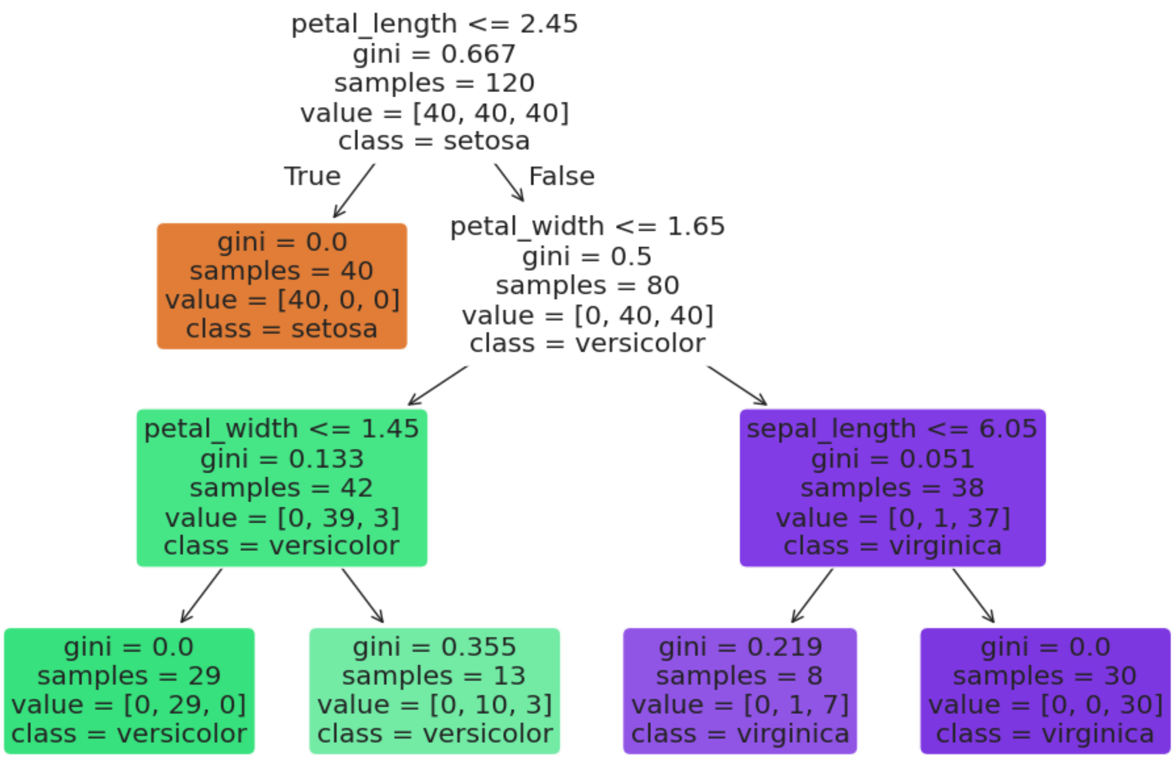
Accuracy, Confusion Matrix and classification report

```
Fitting 5 folds for each of 216 candidates, totalling 1080 fits
Best Parameters: {'criterion': 'gini', 'max_depth': 3, 'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 2}
Test Set Accuracy: 93.33%
```



```
Classification Report (Test):
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       0.90      0.90      0.90        10
           2       0.90      0.90      0.90        10

    accuracy                           0.93        30
   macro avg       0.93      0.93      0.93        30
weighted avg       0.93      0.93      0.93        30
```

Best Decision Tree Visualization

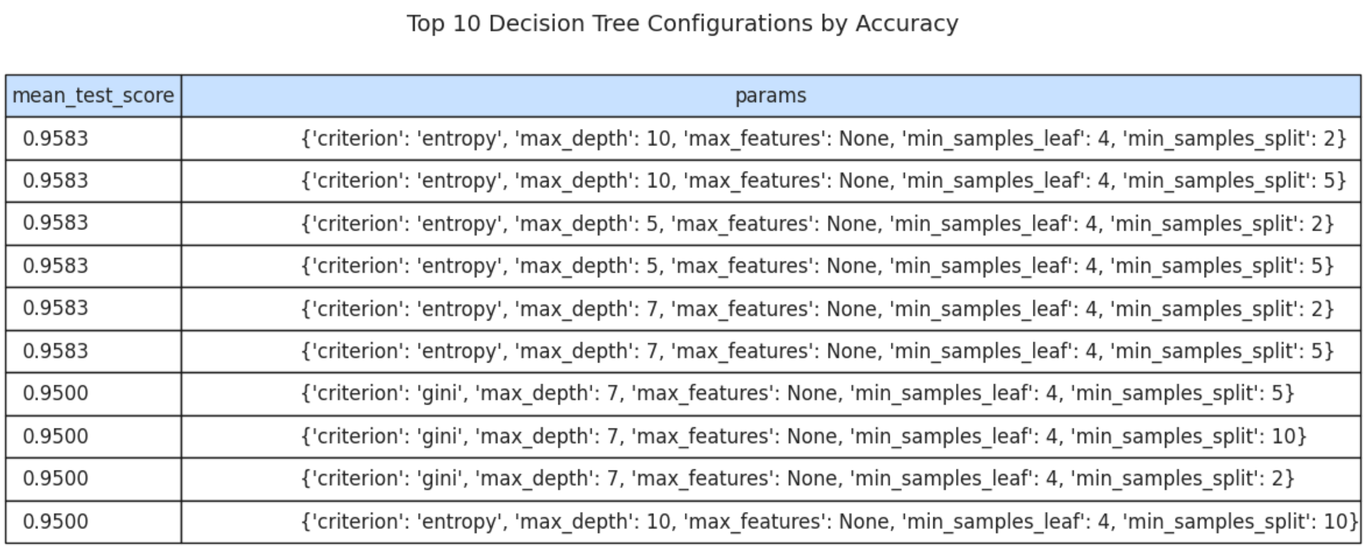


```
Time taken for training and tuning: 4429.3723 ms
```

Plotting mean accuracy Table for various parameters in decision tree

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
# Use Seaborn style
sns.set(style="whitegrid")
# Extract and sort top results
results_df = pd.DataFrame(grid_search.cv_results_)
```

```python
results_df = results_df.sort_values(by='mean_test_score', ascending=False)

# Show top N results
top_n = 10
top_results = results_df.head(top_n)[['mean_test_score', 'params']]
top_results.reset_index(drop=True, inplace=True)
top_results['mean_test_score'] =
top_results['mean_test_score'].apply(lambda x: f"{x:.4f}")
# Create the table plot
fig, ax = plt.subplots(figsize=(12, 5))
ax.axis('off')  # Remove axes
# Create table
table = plt.table(cellText=top_results.values,
                  colLabels=top_results.columns,
                  cellLoc='left',
                  loc='center',
                  colColours=['#cce5ff', '#cce5ff'])  # Light blue header
# Set font size and cell height
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)  # Make rows taller
# Manually adjust column widths
# Narrow the first column (mean_test_score), leave second wider
for (row, col), cell in table.get_celld().items():
    if col == 0:  # mean_test_score
        cell.set_width(0.13)
    elif col == 1:  # params
        cell.set_width(0.87)
# Add title
plt.title(f"Top {top_n} Decision Tree Configurations by Accuracy",
fontsize=14, pad=20)
plt.tight_layout()
plt.show()
```



Top 10 Decision Tree Configurations by Accuracy

mean_test_score	params
0.9583	{'criterion': 'entropy', 'max_depth': 10, 'max_features': None, 'min_samples_leaf': 4, 'min_samples_split': 2}
0.9583	{'criterion': 'entropy', 'max_depth': 10, 'max_features': None, 'min_samples_leaf': 4, 'min_samples_split': 5}
0.9583	{'criterion': 'entropy', 'max_depth': 5, 'max_features': None, 'min_samples_leaf': 4, 'min_samples_split': 2}
0.9583	{'criterion': 'entropy', 'max_depth': 5, 'max_features': None, 'min_samples_leaf': 4, 'min_samples_split': 5}
0.9583	{'criterion': 'entropy', 'max_depth': 7, 'max_features': None, 'min_samples_leaf': 4, 'min_samples_split': 2}
0.9583	{'criterion': 'entropy', 'max_depth': 7, 'max_features': None, 'min_samples_leaf': 4, 'min_samples_split': 5}
0.9500	{'criterion': 'gini', 'max_depth': 7, 'max_features': None, 'min_samples_leaf': 4, 'min_samples_split': 5}
0.9500	{'criterion': 'gini', 'max_depth': 7, 'max_features': None, 'min_samples_leaf': 4, 'min_samples_split': 10}
0.9500	{'criterion': 'gini', 'max_depth': 7, 'max_features': None, 'min_samples_leaf': 4, 'min_samples_split': 2}
0.9500	{'criterion': 'entropy', 'max_depth': 10, 'max_features': None, 'min_samples_leaf': 4, 'min_samples_split': 10}

A **Decision Tree** is a supervised machine learning algorithm used for classification and regression tasks. It works by splitting the data into subsets based on the value of input features, creating a tree-like structure of decision rules.

Each internal node represents a feature (or attribute), each branch represents a decision rule, and each leaf node represents an outcome or class label.
Key Features:

a. Easy to interpret and visualize
b. Non-parametric: No assumptions about data distribution
c. Can handle both numerical and categorical data
d. Prone to overfitting, which can be controlled using parameters like max_depth, min_samples_split, and pruning

Parameter Explanation

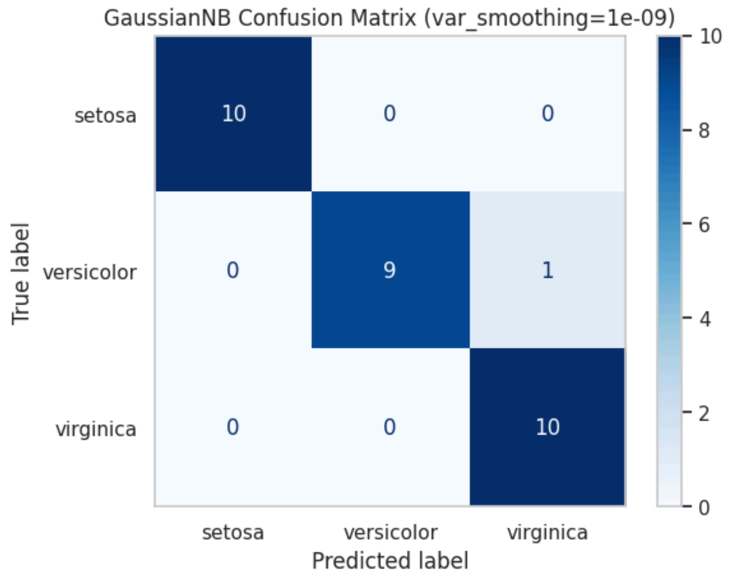
a. <u>max_depth:</u> Limits the maximum depth of the tree to prevent overfitting.
b. <u>min_samples_split:</u> The minimum number of samples required to split an internal node. Increasing this can reduce overfitting.
c. <u>min_samples_leaf:</u> The minimum number of samples required to be at a leaf node. Helps smooth the model predictions.
d. <u>criterion:</u> Function to measure the quality of a split.
    i. 'gini': Gini impurity
    ii. 'entropy': Information gain

e. max_features: The number of features to consider when looking for the best split
    i. 'sqrt': square root of total features
    ii. 'log2': logarithm base 2 of total features
    iii. None: consider all features

8. Importing the model(Gaussian Naive Bayes), training, testing, printing accuracy parameters and measure total time taken to fit and predict the model

```
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
import pandas as pd
import time
# Typical var_smoothing values for GaussianNB (very small values)
var_smoothing_values = [1e-9, 1e-8, 1e-7, 1e-6]
# To store results for summary table
results = []
def train_and_evaluate(nb_classifier, X_train, y_train, X_test, y_test):
    start_time = time.time()
    nb_classifier.fit(X_train, y_train)
    y_pred_train = nb_classifier.predict(X_train)
    y_pred_test = nb_classifier.predict(X_test)
    end_time = time.time()
    train_accuracy = accuracy_score(y_train, y_pred_train)
    test_accuracy = accuracy_score(y_test, y_pred_test)
    time_taken_ms = (end_time - start_time) * 1000
    return train_accuracy, test_accuracy, time_taken_ms, y_pred_test
best_test_accuracy = 0
best_model = None
best_var_smoothing = None
best_y_pred_test = None
for var_smoothing in var_smoothing_values:
    gnb = GaussianNB(var_smoothing=var_smoothing)
    train_acc, test_acc, elapsed_time, y_pred_test = train_and_evaluate(gnb,
X_train, y_train, X_test, y_test)
    results.append({
        "var_smoothing": var_smoothing,
        "train_accuracy": train_acc,
        "test_accuracy": test_acc,
        "time_ms": elapsed_time
    })
    # Track best model
    if test_acc > best_test_accuracy:
        best_test_accuracy = test_acc
        best_model = gnb
        best_var_smoothing = var_smoothing
        best_y_pred_test = y_pred_test
# Detailed evaluation of best model
print(f"\n\n--- Best Model Details ---")
print(f"Best var_smoothing: {best_var_smoothing}")
print(f"Test Accuracy: {best_test_accuracy * 100:.2f}%")
# Confusion matrix and classification report for best model
conf_matrix = confusion_matrix(y_test, best_y_pred_test)
class_report = classification_report(y_test, best_y_pred_test, zero_division=0)
disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix,
                              display_labels=['setosa', 'versicolor', 'virginica'])
disp.plot(cmap='Blues')
plt.title(f"GaussianNB Confusion Matrix (var_smoothing={best_var_smoothing})")
plt.grid(False)
plt.show()
print("\nClassification Report:")
print(class_report)
```

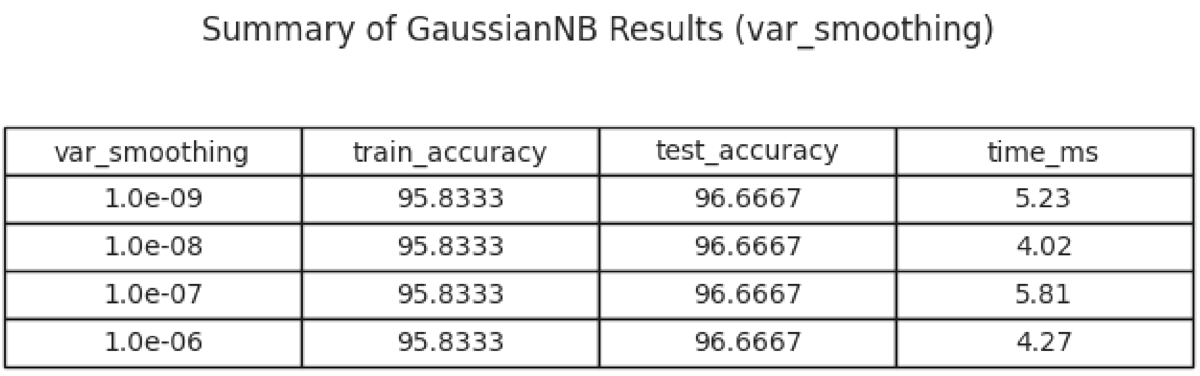
```
--- Best Model Details ---
Best var_smoothing: 1e-09
Test Accuracy: 96.67%
```



```
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       1.00      0.90      0.95        10
           2       0.91      1.00      0.95        10

    accuracy                           0.97        30
   macro avg       0.97      0.97      0.97        30
weighted avg       0.97      0.97      0.97        30
```

Plotting Table for GausianNB for different parameters

```python
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# After collecting results into `results` list:

df_results = pd.DataFrame(results)

# Format var_smoothing in scientific notation string format for display
df_results_display = df_results.copy()
df_results_display['var_smoothing'] = df_results_display['var_smoothing'].apply(lambda x:
f"{x:.1e}")
df_results_display['train_accuracy'] = df_results_display['train_accuracy'] * 100
df_results_display['test_accuracy'] = df_results_display['test_accuracy'] * 100
df_results_display['time_ms'] = df_results_display['time_ms'].round(2)

plt.figure(figsize=(8, 1 + 0.4 * len(df_results)))  # height grows with rows
plt.title("Summary of GaussianNB Results (var_smoothing)")

table = plt.table(cellText=df_results_display.round(4).values,
                  colLabels=df_results_display.columns,
                  cellLoc='center',
                  loc='center')

table.auto_set_font_size(False)
table.set_fontsize(10)
table.scale(1, 1.5)

plt.axis('off')
plt.show()
```



Summary of GaussianNB Results (var_smoothing)

var_smoothing	train_accuracy	test_accuracy	time_ms
1.0e-09	95.8333	96.6667	5.23
1.0e-08	95.8333	96.6667	4.02
1.0e-07	95.8333	96.6667	5.81
1.0e-06	95.8333	96.6667	4.27

Gaussian Naive Bayes (GaussianNB):

GaussianNB is a supervised machine learning algorithm based on Bayes' Theorem, assuming that the features follow a normal (Gaussian) distribution. It is commonly used for classification tasks. It calculates the probability of each class given the input features, assuming feature independence. Works well with continuous numeric features that are normally distributed.

Key Features:

a. Simple and fast for large datasets
b. Works well with normally distributed data
c. Assumes feature independence (naive assumption)
d. Performs well with high-dimensional data
e. Sensitive to non-Gaussian distributions

Parameter Description:

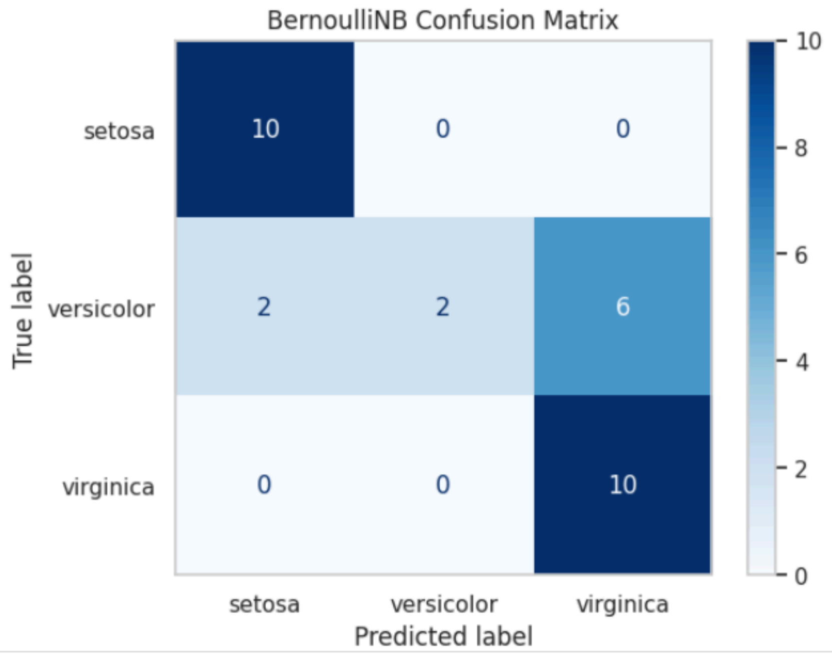
var_smoothing: Portion of the largest variance added to all features' variances for stability (default: 1e-9). Helps prevent division by zero and overfitting to small variances.

9. **Importing the model(Bernoulli Naive Bayes), training, testing, printing accuracy parameters and measure total time taken to fit and predict the model**

```
from sklearn.naive_bayes import BernoulliNB
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
import time

# Apply StandardScaler for better scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Set up the parameter grid for hyperparameter tuning
param_grid = {
    'alpha': [0.001, 0.005, 0.01, 0.05, 0.1],  # Laplace smoothing
    'binarize': [0.05, 0.1, 0.15, 0.2],        # Thresholds for binarization
    'fit_prior': [True, False],                 # Use prior probabilities or not
}

# Initialize BernoulliNB
bnb = BernoulliNB()

start_time = time.time()

# Perform Grid Search with cross-validation
```

```python
grid_search = GridSearchCV(estimator=bnb, param_grid=param_grid, cv=5,
scoring='accuracy', n_jobs=-1)
grid_search.fit(X_train_scaled, y_train)

# Best parameters and best estimator
best_params = grid_search.best_params_
print(f"Best parameters for BernoulliNB: {best_params}")
best_bnb = grid_search.best_estimator_

# Predict on test data
y_pred_test = best_bnb.predict(X_test_scaled)

end_time = time.time()
time_taken_ms = (end_time - start_time) * 1000

# Evaluate the model (test only)
test_accuracy = accuracy_score(y_test, y_pred_test)
conf_matrix = confusion_matrix(y_test, y_pred_test)
class_report = classification_report(y_test, y_pred_test)

print(f"BernoulliNB (best parameters) Test Accuracy: {test_accuracy * 100:.2f}%")

# Since train accuracy removed, skip overfitting check

print("\nBernoulliNB Confusion Matrix:")
disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix,
                              display_labels=['setosa', 'versicolor', 'virginica'])
disp.plot(cmap='Blues')
plt.title("BernoulliNB Confusion Matrix")
plt.grid(False)
plt.show()
print("\nBernoulliNB Classification Report:")
print(class_report)
print(f"Time taken for training and tuning: {time_taken_ms:.4f} ms")
```

```
Best parameters for BernoulliNB: {'alpha': 0.001, 'binarize': 0.05, 'fit_prior': True}
BernoulliNB (best parameters) Test Accuracy: 73.33%

BernoulliNB Confusion Matrix:
```

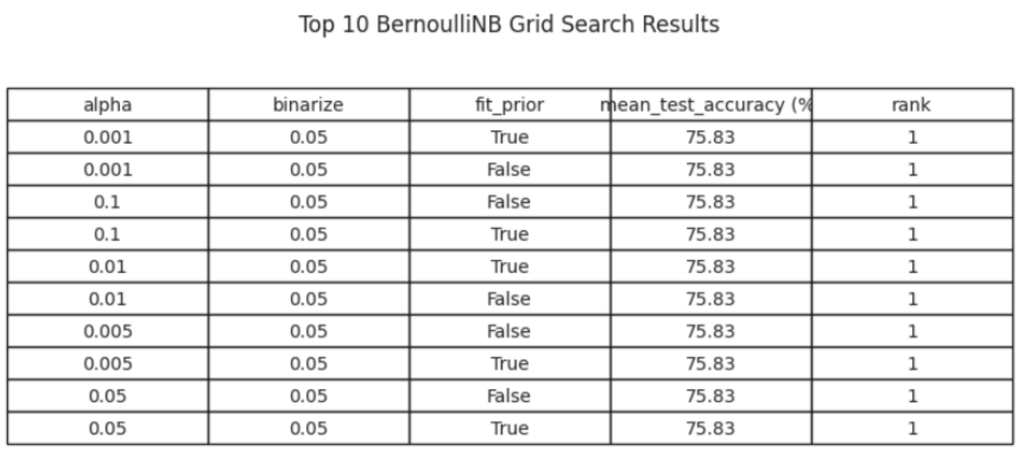


```
BernoulliNB Classification Report:
              precision    recall  f1-score   support

           0       0.83      1.00      0.91        10
           1       1.00      0.20      0.33        10
           2       0.62      1.00      0.77        10

    accuracy                           0.73        30
   macro avg       0.82      0.73      0.67        30
weighted avg       0.82      0.73      0.67        30

Time taken for training and tuning: 2604.7769 ms
```

Plotting Table for BernoulliNB for different parameters

```python
import pandas as pd
import matplotlib.pyplot as plt
# Extract GridSearchCV results
cv_results = grid_search.cv_results_
# Create a DataFrame with selected columns
results_df = pd.DataFrame({
    'alpha': cv_results['param_alpha'],
    'binarize': cv_results['param_binarize'],
    'fit_prior': cv_results['param_fit_prior'],
    'mean_test_accuracy (%)': cv_results['mean_test_score'] * 100,
    'rank': cv_results['rank_test_score']
})
# Sort by best performance
results_df = results_df.sort_values(by='mean_test_accuracy (%)',
ascending=False).reset_index(drop=True)
# Round for display
```

```
results_df_display = results_df.copy()
results_df_display['mean_test_accuracy (%)'] = results_df_display['mean_test_accuracy
(%)'].round(2)
# Limit to top 10
top_10_results = results_df_display.head(10)
# Plot as a table
plt.figure(figsize=(10, 0.5 + 0.4 * len(top_10_results)))  # auto height
plt.title("Top 10 BernoulliNB Grid Search Results")
table = plt.table(cellText=top_10_results.values,
                  colLabels=top_10_results.columns,
                  cellLoc='center',
                  loc='center')
table.auto_set_font_size(False)
table.set_fontsize(10)
table.scale(1, 1.5)
plt.axis('off')
plt.show()
```



Top 10 BernoulliNB Grid Search Results

alpha	binarize	fit_prior	mean_test_accuracy (%	rank
0.001	0.05	True	75.83	1
0.001	0.05	False	75.83	1
0.1	0.05	False	75.83	1
0.1	0.05	True	75.83	1
0.01	0.05	True	75.83	1
0.01	0.05	False	75.83	1
0.005	0.05	False	75.83	1
0.005	0.05	True	75.83	1
0.05	0.05	False	75.83	1
0.05	0.05	True	75.83	1

Bernoulli Naive Bayes (BernoulliNB)

BernoulliNB is a variant of Naive Bayes that is designed for binary/boolean features (i.e., features are either 0 or 1). It’s commonly used for text classification with binary word occurrence. Suitable when features are binary (e.g., whether a word appears in a document) Useful in problems where absence/presence of a feature is more informative than frequency

Key Features:

a. Efficient for binary feature spaces
b. Performs well on text classification with binary features
c. Makes binary assumptions about features
d. Sensitive to how features are binarized

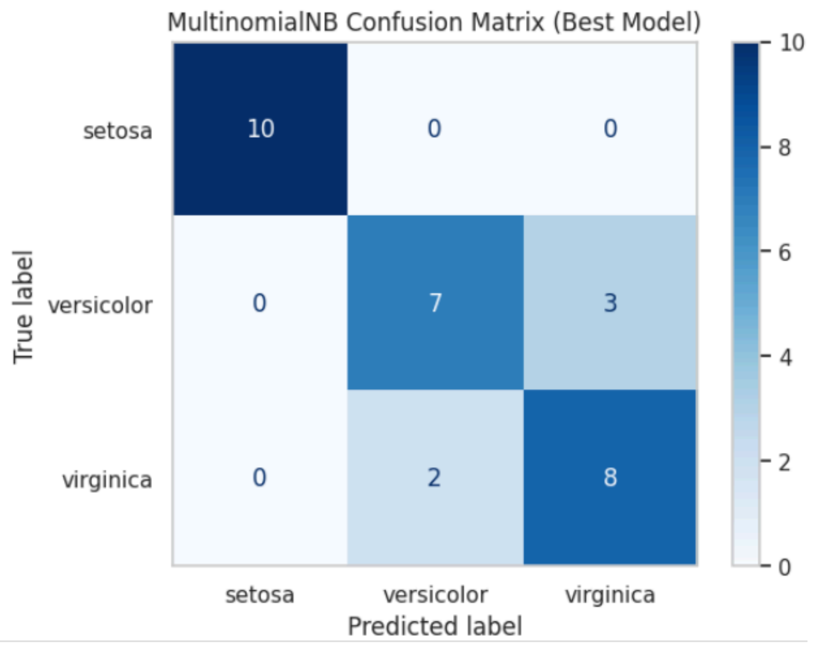
Parameter	Description:
alpha	Laplace smoothing parameter. Prevents zero probabilities (default: 1.0).
binarize	Threshold for binarizing numeric features. Features above this threshold are 1, else 0.
fit_prior	Whether to learn class prior probabilities from training data. If False, assumes uniform class priors.

10. Importing the model(Multinomial Naive Bayes), training, testing, printing accuracy parameters and measure total time taken to fit and predict the model

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report,
ConfusionMatrixDisplay
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import GridSearchCV
import matplotlib.pyplot as plt
import time

# Scale X_train and X_test to ensure non-negative values
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize the MultinomialNB classifier
mnb = MultinomialNB()

# Set up parameter grid for GridSearchCV
param_grid = {
    'alpha': [0.001, 0.01, 0.1, 1]
}

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

# Train the model with hyperparameter tuning
start_time = time.time()
grid_search.fit(X_train_scaled, y_train)
end_time = time.time()

# Best model from GridSearchCV
best_mnb = grid_search.best_estimator_

# Predict on the test data
y_pred_test = best_mnb.predict(X_test_scaled)

# Evaluate the model
test_accuracy = accuracy_score(y_test, y_pred_test)
```

```
conf_matrix = confusion_matrix(y_test, y_pred_test)
class_report = classification_report(y_test, y_pred_test, zero_division=0)

# Print best params and results
print(f"Best alpha parameter: {grid_search.best_params_['alpha']}")
print(f"Test Set Accuracy: {test_accuracy * 100:.2f}%")

print("\nConfusion Matrix:")
disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix,
                              display_labels=['setosa', 'versicolor', 'virginica'])
disp.plot(cmap='Blues')
plt.title("MultinomialNB Confusion Matrix (Best Model)")
plt.grid(False)
plt.show()

print("\nClassification Report:")
print(class_report)

time_taken_ms = (end_time - start_time) * 1000
print(f"\nTime taken for training and tuning: {time_taken_ms:.4f} ms")
```

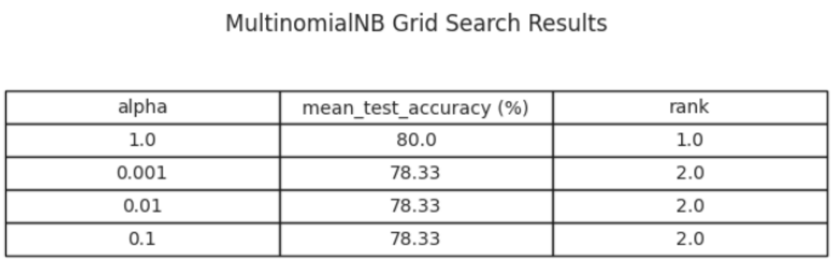
```
Best alpha parameter: 1
Test Set Accuracy: 83.33%

Confusion Matrix:
```



```
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       0.78      0.70      0.74        10
           2       0.73      0.80      0.76        10

    accuracy                           0.83        30
   macro avg       0.84      0.83      0.83        30
weighted avg       0.84      0.83      0.83        30


Time taken for training and tuning: 2770.1128 ms
```

Plotting Table for MultinomialNB for different parameters

```
import pandas as pd
import matplotlib.pyplot as plt
# Extract cv_results from GridSearchCV
cv_results = grid_search.cv_results_
# Create a DataFrame with relevant information
results_df = pd.DataFrame({
    'alpha': cv_results['param_alpha'],
    'mean_test_accuracy (%)': cv_results['mean_test_score'] * 100,
    'rank': cv_results['rank_test_score']
})
# Sort by best accuracy
results_df = results_df.sort_values(by='mean_test_accuracy (%)',
ascending=False).reset_index(drop=True)
# Round for clean display
results_df_display = results_df.copy()
results_df_display['mean_test_accuracy (%)'] =
results_df_display['mean_test_accuracy (%)'].round(2)
# Plot the table
plt.figure(figsize=(8, 1 + 0.4 * len(results_df_display)))
plt.title("MultinomialNB Grid Search Results")

table = plt.table(cellText=results_df_display.values,
                  colLabels=results_df_display.columns,
                  cellLoc='center',
                  loc='center')

table.auto_set_font_size(False)
table.set_fontsize(10)
table.scale(1, 1.5)
plt.axis('off')
plt.show()
```


MultinomialNB Grid Search Results

alpha	mean_test_accuracy (%)	rank
1.0	80.0	1.0
0.001	78.33	2.0
0.01	78.33	2.0
0.1	78.33	2.0

Multinomial Naive Bayes (MultinomialNB)
MultinomialNB is suitable for discrete feature counts such as word frequencies in text classification (e.g., spam filtering, sentiment analysis). It models the distribution of feature counts (not binary values) Works best with count data (e.g., bag-of-words or TF-IDF)
Key Features:

a. Works well for text data and document classification
b. Assumes feature counts are conditionally independent given the class
c. Handles multi-class classification efficiently
d. Sensitive to zero counts (use of smoothing is crucial)

Parameter Description:

Parameter	Description
alpha	Laplace smoothing parameter (default: 1.0). Helps handle zero counts in training data.
fit_prior	Whether to learn class prior probabilities from training data. If False, use uniform priors.

Discussion on IRIS dataset:
On evaluating different classification algorithms on the Iris dataset, we observe notable differences in performance that stem largely from the nature of the dataset and the assumptions made by each model. The Iris dataset comprises 150 samples with 4 continuous numerical features and 3 distinct classes representing species of iris flowers. Due to its balanced structure and well-separated classes, it is often used as a benchmark for testing classification models.

- The Decision Tree classifier performed well, achieving a test accuracy of 93.33% with an optimal parameter configuration including criterion='gini', max_depth=3, and max_features='sqrt'. The model provided balanced precision, recall, and F1-scores across all classes. Its interpretability makes it especially useful when understanding the model's decisions is important. However, the limited depth, while helping to prevent overfitting, may slightly reduce its ability to capture complex class boundaries in some cases.

- The Gaussian Naive Bayes (GaussianNB) model emerged as the most effective, with a test accuracy of 96.67% and a macro-averaged F1-score of 0.97. It leveraged the assumption that features follow a Gaussian distribution—a reasonable assumption for the Iris dataset's continuous features. Its performance was particularly strong due to its simplicity, low computational cost, and suitability for small, well-structured datasets. GaussianNB also demonstrated high class-wise precision and recall, particularly excelling in correctly classifying all instances of class 0 and achieving near-perfect scores for the other two classes.

- In contrast, the Bernoulli Naive Bayes (BernoulliNB) model performed poorly, with an accuracy of only 73.33% and a macro F1-score of 0.67. Designed primarily for binary feature inputs, BernoulliNB is not well-suited for continuous data like that in the Iris dataset. Even with appropriate binarization and hyperparameter tuning (alpha=0.001, binarize=0.05), it struggled particularly with class 1, showing a recall of just 0.20. This highlights the limitations of applying a model built for binary input to real-valued features.

- The Multinomial Naive Bayes (MultinomialNB) model offered moderate performance, achieving a test accuracy of 83.33%. Although better than BernoulliNB, it was noticeably behind GaussianNB and Decision Tree. MultinomialNB assumes discrete count-based features (like word frequencies), which misaligns with the real-valued, continuous nature of the Iris dataset. While it handled class 0 perfectly, it showed slightly weaker recall and precision for classes 1 and 2.

In conclusion, GaussianNB proved to be the most effective model for the Iris dataset, thanks to its compatibility with continuous data and minimal training complexity. Decision Trees also performed robustly and offer the added benefit of interpretability. In contrast, both BernoulliNB and MultinomialNB underperformed due to their assumptions about input feature types, which do not align well with the characteristics of the Iris dataset. This analysis reinforces the importance of selecting models that align with the data's structure and distribution.

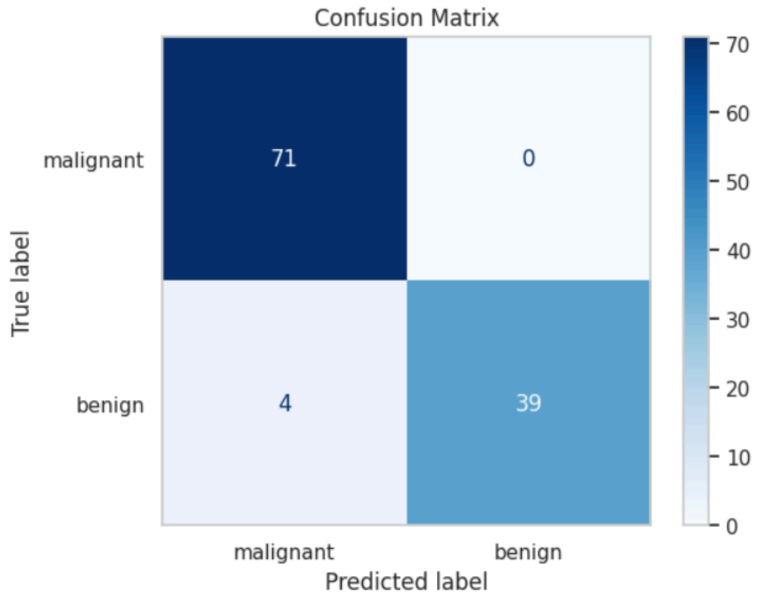
1. Download, Load and Inspect Breast Cancer Dataset from CSV

```
import pandas as pd
from ucimlrepo import fetch_ucirepo

# Fetch the dataset
breast_cancer_wisconsin_diagnostic = fetch_ucirepo(id=17)

# Extract features and targets
X = breast_cancer_wisconsin_diagnostic.data.features
y = breast_cancer_wisconsin_diagnostic.data.targets

# Combine features and targets into a single DataFrame
df2 = pd.concat([X, y], axis=1)

# Save the combined DataFrame to a CSV file
df2.to_csv('breast_cancer_wisconsin.csv', index=False)

print("Dataset successfully converted and saved to 'breast_cancer_wisconsin.csv'")
```

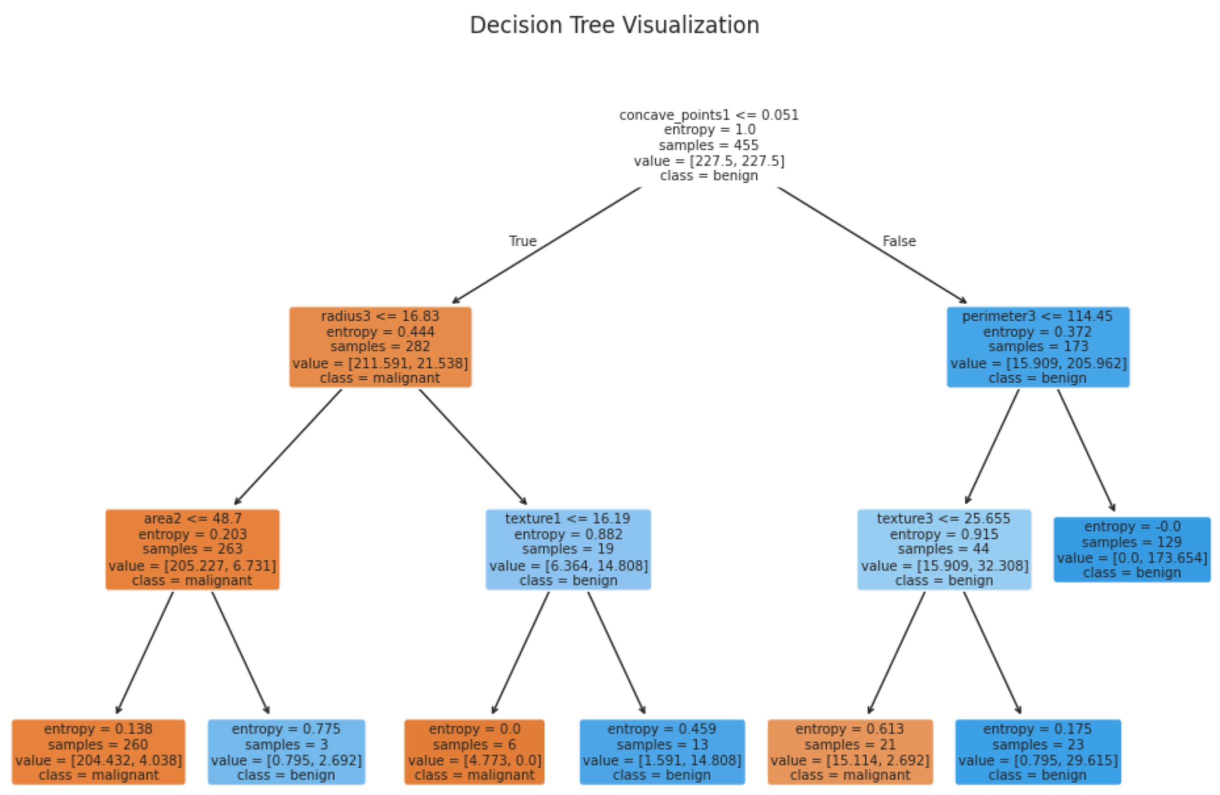
2. Importing the model(Decision Tree), training, testing, printing accuracy parameters

```
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report,
roc_auc_score, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
import time

X = df2.drop(columns=['Diagnosis'])
y = df2['Diagnosis']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize DecisionTreeClassifier without parameters for GridSearch
dt_classifier = DecisionTreeClassifier(random_state=42, class_weight='balanced',
criterion='entropy')

# Parameter grid for GridSearchCV
param_grid = {
    'max_depth': [3, 5, 7, 10],
    'min_samples_split': [2, 3, 5],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['sqrt', 'log2', None]
}

grid_search = GridSearchCV(estimator=dt_classifier, param_grid=param_grid, cv=5,
scoring='accuracy', n_jobs=-1)
start_time = time.time()
grid_search.fit(X_train, y_train)
end_time = time.time()

print(f"Best parameters from GridSearchCV: {grid_search.best_params_}")

# Use the best estimator for predictions
best_dt = grid_search.best_estimator_

y_pred_test = best_dt.predict(X_test)

test_accuracy = accuracy_score(y_test, y_pred_test)
conf_matrix = confusion_matrix(y_test, y_pred_test)
class_report = classification_report(y_test, y_pred_test)

print(f"Test Set Accuracy: {test_accuracy * 100:.2f}%")

print("\nConfusion Matrix:")
disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix,
                              display_labels=['malignant', 'benign'])
disp.plot(cmap='Blues')
plt.grid(False)
plt.title("Confusion Matrix")
plt.show()

print("\nClassification Report:")
print(class_report)

print("ROC-AUC:", roc_auc_score(y_test, best_dt.predict_proba(X_test)[:, 1]))

plt.figure(figsize=(12, 8))
plot_tree(best_dt,
          filled=True,
          feature_names=X.columns,
          class_names=['malignant', 'benign'],
          rounded=True)
plt.title("Decision Tree Visualization")
plt.show()

time_taken_ms = (end_time - start_time) * 1000
print(f"\nTime taken for GridSearchCV, training and prediction:{time_taken_ms:.4f} ms")
```

```
Best parameters from GridSearchCV: {'max_depth': 3, 'max_features': None, 'min_samples_leaf': 1, 'min_samples_split': 2}
Test Set Accuracy: 96.49%

Confusion Matrix:
```



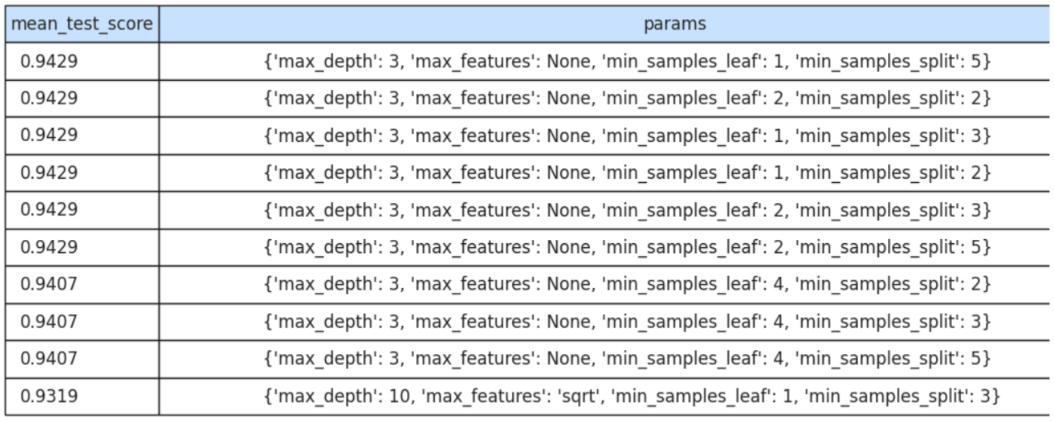
```
Classification Report:
              precision    recall  f1-score   support

           B       0.95      1.00      0.97        71
           M       1.00      0.91      0.95        43

    accuracy                           0.96       114
   macro avg       0.97      0.95      0.96       114
weighted avg       0.97      0.96      0.96       114

ROC-AUC: 0.9715034392400917
```



```
Time taken for GridSearchCV, training and prediction: 10177.6633 ms
```

Plotting mean accuracy Table for various parameters in decision tree

```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Use Seaborn style
sns.set(style="whitegrid")

# Extract and sort top results
results_df = pd.DataFrame(grid_search.cv_results_)

results_df = results_df.sort_values(by='mean_test_score', ascending=False)

# Show top N results
top_n = 10
top_results = results_df.head(top_n)[['mean_test_score', 'params']]
top_results.reset_index(drop=True, inplace=True)
top_results['mean_test_score'] =
top_results['mean_test_score'].apply(lambda x: f"{x:.4f}")

# Create the table plot
fig, ax = plt.subplots(figsize=(12, 5))
ax.axis('off')  # Remove axes

# Create table
table = plt.table(cellText=top_results.values,
                 colLabels=top_results.columns,
                 cellLoc='left',
                 loc='center',
                 colColours=['#cce5ff', '#cce5ff'])  # Light blue header

# Set font size and cell height
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)  # Make rows taller

# Manually adjust column widths
# Narrow the first column (mean_test_score), leave second wider
for (row, col), cell in table.get_celld().items():
    if col == 0:  # mean_test_score
        cell.set_width(0.13)
    elif col == 1:  # params
        cell.set_width(0.87)

# Add title
plt.title(f"Top {top_n} Decision Tree Configurations by Accuracy",
fontsize=14, pad=20)

plt.tight_layout()
plt.show()
```



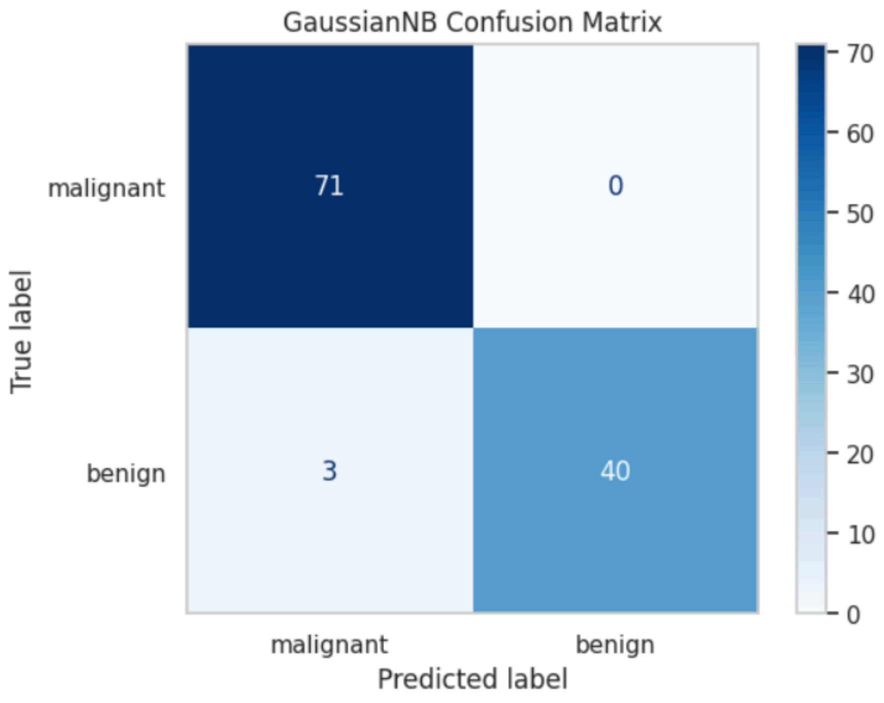
mean_test_score	params
0.9429	{'max_depth': 3, 'max_features': None, 'min_samples_leaf': 1, 'min_samples_split': 5}
0.9429	{'max_depth': 3, 'max_features': None, 'min_samples_leaf': 2, 'min_samples_split': 2}
0.9429	{'max_depth': 3, 'max_features': None, 'min_samples_leaf': 1, 'min_samples_split': 3}
0.9429	{'max_depth': 3, 'max_features': None, 'min_samples_leaf': 1, 'min_samples_split': 2}
0.9429	{'max_depth': 3, 'max_features': None, 'min_samples_leaf': 2, 'min_samples_split': 3}
0.9429	{'max_depth': 3, 'max_features': None, 'min_samples_leaf': 2, 'min_samples_split': 5}
0.9407	{'max_depth': 3, 'max_features': None, 'min_samples_leaf': 4, 'min_samples_split': 2}
0.9407	{'max_depth': 3, 'max_features': None, 'min_samples_leaf': 4, 'min_samples_split': 3}
0.9407	{'max_depth': 3, 'max_features': None, 'min_samples_leaf': 4, 'min_samples_split': 5}
0.9319	{'max_depth': 10, 'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 3}

3. **Importing the model(Gaussian Naive Bayes), training, testing, printing accuracy parameters and measure total time taken to fit and predict the model**

```
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
import time
# Parameter grid for var_smoothing
param_grid = {'var_smoothing': [1e-9, 1e-8, 1e-7, 1e-6, 1e-5]}
gnb = GaussianNB()
grid_search = GridSearchCV(estimator=gnb, param_grid=param_grid, cv=5,
scoring='accuracy', n_jobs=-1)
start_time = time.time()
grid_search.fit(X_train, y_train)
end_time = time.time()
best_gnb = grid_search.best_estimator_
print(f"Best var_smoothing parameter:
{grid_search.best_params_['var_smoothing']}")
# Predict on test data
y_pred_test = best_gnb.predict(X_test)
# Evaluate
test_accuracy = accuracy_score(y_test, y_pred_test)
conf_matrix = confusion_matrix(y_test, y_pred_test)
class_report = classification_report(y_test, y_pred_test)
print(f"\nTest Set Accuracy: {test_accuracy * 100:.2f}%")
print("\nConfusion Matrix:")
disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix,
                              display_labels=['malignant', 'benign'])
```

```
disp.plot(cmap='Blues')
plt.grid(False)
plt.title("GaussianNB Confusion Matrix")
plt.show()
print("\nClassification Report:")
print(class_report)
time_taken_ms = (end_time - start_time) * 1000
print(f"\nTime taken for GridSearchCV, training and prediction:
{time_taken_ms:.4f} ms")
```

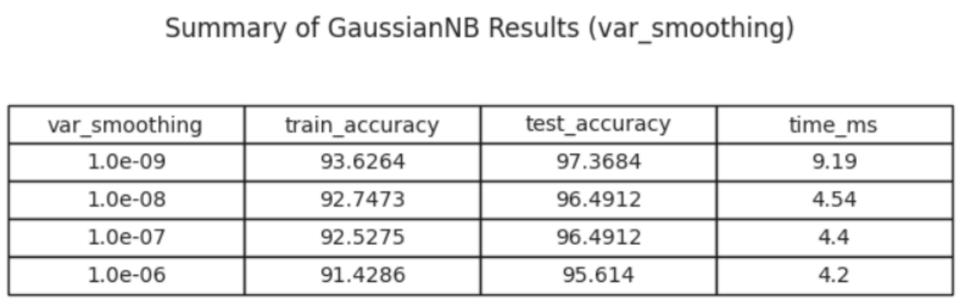
```
Best var_smoothing parameter: 1e-09

Test Set Accuracy: 97.37%

Confusion Matrix:
```



```
Classification Report:
              precision    recall  f1-score   support

           B       0.96      1.00      0.98        71
           M       1.00      0.93      0.96        43

    accuracy                           0.97       114
   macro avg       0.98      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114


Time taken for GridSearchCV, training and prediction: 138.1164 ms
```

Plotting Table for GausianNB for different parameters

```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# After collecting results into `results` list:

df_results = pd.DataFrame(results)

# Format var_smoothing in scientific notation string format for display
df_results_display = df_results.copy()
df_results_display['var_smoothing'] =
df_results_display['var_smoothing'].apply(lambda x: f"{x:.1e}")
df_results_display['train_accuracy'] = df_results_display['train_accuracy']
* 100
df_results_display['test_accuracy'] = df_results_display['test_accuracy'] *
100
df_results_display['time_ms'] = df_results_display['time_ms'].round(2)

plt.figure(figsize=(8, 1 + 0.4 * len(df_results)))  # height grows with
rows
plt.title("Summary of GaussianNB Results (var_smoothing)")

table = plt.table(cellText=df_results_display.round(4).values,
                  colLabels=df_results_display.columns,
                  cellLoc='center',
                  loc='center')

table.auto_set_font_size(False)
table.set_fontsize(10)
table.scale(1, 1.5)

plt.axis('off')
plt.show()
```

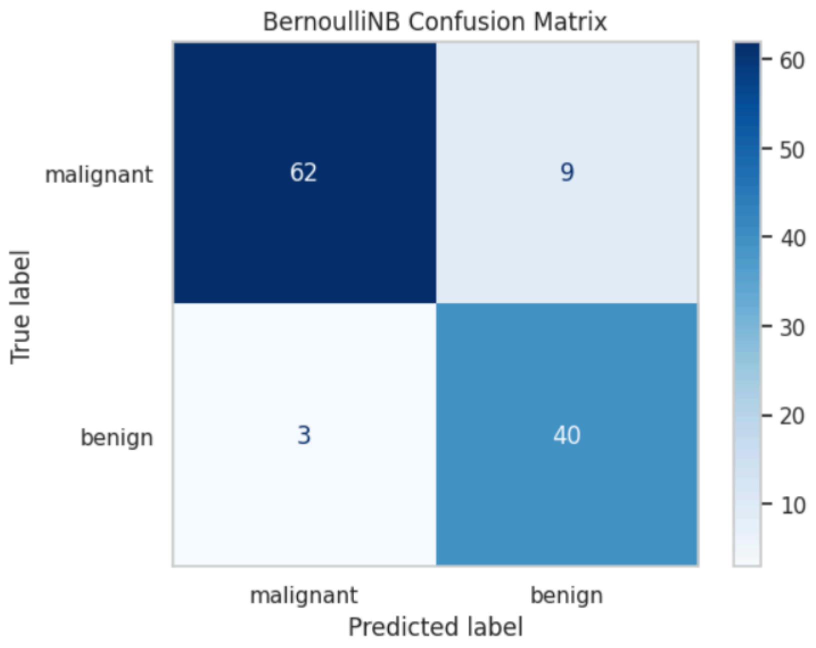

Summary of GaussianNB Results (var_smoothing)

var_smoothing	train_accuracy	test_accuracy	time_ms
1.0e-09	93.6264	97.3684	9.19
1.0e-08	92.7473	96.4912	4.54
1.0e-07	92.5275	96.4912	4.4
1.0e-06	91.4286	95.614	4.2

4. Importing the model(Bernoulli Naive Bayes), training, testing, printing accuracy parameters and measure total time taken to fit and predict the model

```
from sklearn.naive_bayes import BernoulliNB
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
import time

# Define parameter grid for GridSearchCV
param_grid = {
    'alpha': [0.001, 0.01, 0.1, 1.0],
    'binarize': [0.0, 0.05, 0.1, 0.15],
    'fit_prior': [True, False]
}

bnb = BernoulliNB()

grid_search = GridSearchCV(estimator=bnb, param_grid=param_grid, cv=5,
scoring='accuracy', n_jobs=-1)

start_time = time.time()
grid_search.fit(X_train, y_train)
end_time = time.time()

best_bnb = grid_search.best_estimator_

print(f"Best parameters: {grid_search.best_params_}")

# Predict on test data
y_pred_test = best_bnb.predict(X_test)

# Evaluate
test_accuracy = accuracy_score(y_test, y_pred_test)
conf_matrix = confusion_matrix(y_test, y_pred_test)
class_report = classification_report(y_test, y_pred_test, zero_division=0)

print(f"\nTest Set Accuracy: {test_accuracy * 100:.2f}%")

print("\nConfusion Matrix:")
disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix,
                              display_labels=['malignant', 'benign'])
disp.plot(cmap='Blues')
plt.grid(False)
plt.title("BernoulliNB Confusion Matrix")
plt.show()

print("\nClassification Report:")
print(class_report)

time_taken_ms = (end_time - start_time) * 1000
print(f"\nTime taken for GridSearchCV, training and prediction: {time_taken_ms:.4f}
ms")
```

```
Best parameters: {'alpha': 0.001, 'binarize': 0.05, 'fit_prior': True}

Test Set Accuracy: 89.47%

Confusion Matrix:
```

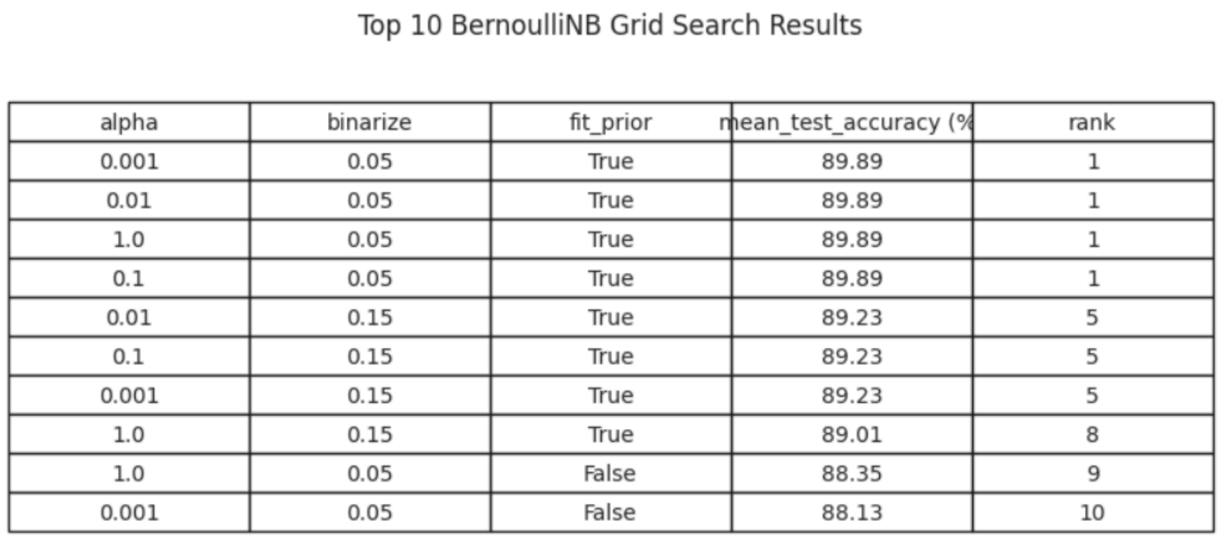


```
Classification Report:
              precision    recall  f1-score   support

           B       0.95      0.87      0.91        71
           M       0.82      0.93      0.87        43

    accuracy                           0.89       114
   macro avg       0.89      0.90      0.89       114
weighted avg       0.90      0.89      0.90       114


Time taken for GridSearchCV, training and prediction: 849.2913 ms
```

Plotting Table for BernoulliNB for different parameters

```
import pandas as pd
import matplotlib.pyplot as plt
```

```python
# Extract GridSearchCV results
cv_results = grid_search.cv_results_
# Create a DataFrame with selected columns
results_df = pd.DataFrame({
    'alpha': cv_results['param_alpha'],
    'binarize': cv_results['param_binarize'],
    'fit_prior': cv_results['param_fit_prior'],
    'mean_test_accuracy (%)': cv_results['mean_test_score'] * 100,
    'rank': cv_results['rank_test_score']
})
# Sort by best performance
results_df = results_df.sort_values(by='mean_test_accuracy (%)',
ascending=False).reset_index(drop=True)
# Round for display
results_df_display = results_df.copy()
results_df_display['mean_test_accuracy (%)'] =
results_df_display['mean_test_accuracy (%)'].round(2)
# Limit to top 10
top_10_results = results_df_display.head(10)
# Plot as a table
plt.figure(figsize=(10, 0.5 + 0.4 * len(top_10_results)))  # auto height
plt.title("Top 10 BernoulliNB Grid Search Results")
table = plt.table(cellText=top_10_results.values,
                  colLabels=top_10_results.columns,
                  cellLoc='center',
                  loc='center')
table.auto_set_font_size(False)
table.set_fontsize(10)
table.scale(1, 1.5)
plt.axis('off')
plt.show()
```


Top 10 BernoulliNB Grid Search Results

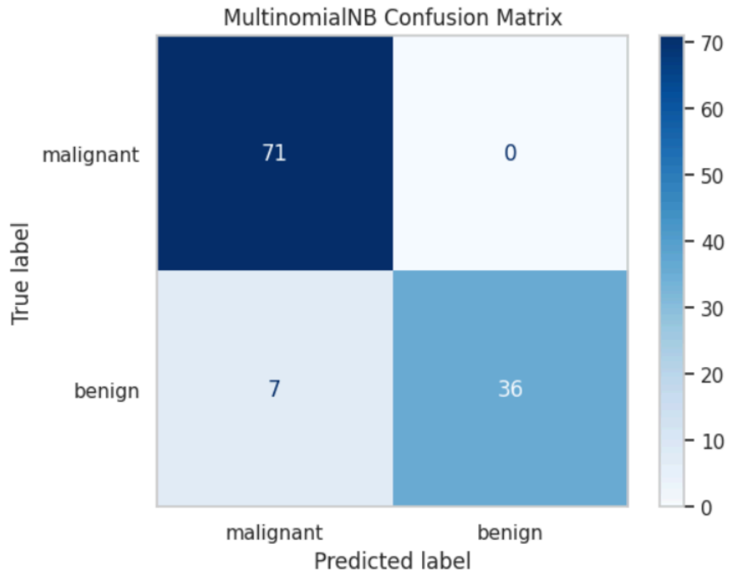
alpha	binarize	fit_prior	mean_test_accuracy (%	rank
0.001	0.05	True	89.89	1
0.01	0.05	True	89.89	1
1.0	0.05	True	89.89	1
0.1	0.05	True	89.89	1
0.01	0.15	True	89.23	5
0.1	0.15	True	89.23	5
0.001	0.15	True	89.23	5
1.0	0.15	True	89.01	8
1.0	0.05	False	88.35	9
0.001	0.05	False	88.13	10

5. Importing the model(Multinomial Naive Bayes), training, testing, printing accuracy parameters and measure total time taken to fit and predict the model

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report,
ConfusionMatrixDisplay
import matplotlib.pyplot as plt
import time

# Parameter grid for GridSearchCV
param_grid = {
    'alpha': [0.001, 0.01, 0.1, 1.0],
    'fit_prior': [True, False]
}

mnb = MultinomialNB()

grid_search = GridSearchCV(estimator=mnb, param_grid=param_grid, cv=5, scoring='accuracy',
n_jobs=-1)

start_time = time.time()
grid_search.fit(X_train, y_train)
end_time = time.time()

best_mnb = grid_search.best_estimator_

print(f"Best parameters: {grid_search.best_params_}")

# Predict on test data
y_pred_test = best_mnb.predict(X_test)

# Evaluate
test_accuracy = accuracy_score(y_test, y_pred_test)
conf_matrix = confusion_matrix(y_test, y_pred_test)
class_report = classification_report(y_test, y_pred_test, zero_division=0)

print(f"\nTest Set Accuracy: {test_accuracy * 100:.2f}%")

print("\nConfusion Matrix:")
disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix,
                              display_labels=['malignant', 'benign'])
disp.plot(cmap='Blues')
plt.grid(False)
plt.title("MultinomialNB Confusion Matrix")
plt.show()

print("\nClassification Report:")
print(class_report)

time_taken_ms = (end_time - start_time) * 1000
```

```
print(f"\nTime taken for GridSearchCV, training and prediction: {time_taken_ms:.4f} ms")
```

```
Best parameters: {'alpha': 0.001, 'fit_prior': True}

Test Set Accuracy: 93.86%

Confusion Matrix:
```

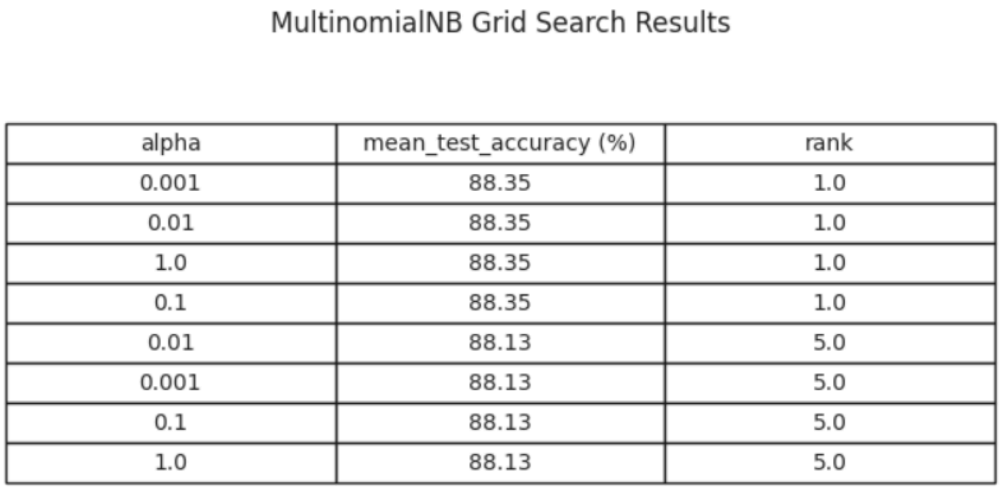


```
Classification Report:
              precision    recall  f1-score   support

           B       0.91      1.00      0.95        71
           M       1.00      0.84      0.91        43

    accuracy                           0.94       114
   macro avg       0.96      0.92      0.93       114
weighted avg       0.94      0.94      0.94       114


Time taken for GridSearchCV, training and prediction: 230.9201 ms
```

Plotting Table for MultinomialNB for different parameters

```
import pandas as pd
import matplotlib.pyplot as plt

# Extract cv_results from GridSearchCV
cv_results = grid_search.cv_results_

# Create a DataFrame with relevant information
results_df = pd.DataFrame({
    'alpha': cv_results['param_alpha'],
    'mean_test_accuracy (%)': cv_results['mean_test_score'] * 100,
    'rank': cv_results['rank_test_score']
})
```

```
# Sort by best accuracy
results_df = results_df.sort_values(by='mean_test_accuracy (%)',
ascending=False).reset_index(drop=True)

# Round for clean display
results_df_display = results_df.copy()
results_df_display['mean_test_accuracy (%)'] =
results_df_display['mean_test_accuracy (%)'].round(2)

# Plot the table
plt.figure(figsize=(8, 1 + 0.4 * len(results_df_display)))
plt.title("MultinomialNB Grid Search Results")

table = plt.table(cellText=results_df_display.values,
                  colLabels=results_df_display.columns,
                  cellLoc='center',
                  loc='center')

table.auto_set_font_size(False)
table.set_fontsize(10)
table.scale(1, 1.5)

plt.axis('off')
plt.show()
```



MultinomialNB Grid Search Results

alpha	mean_test_accuracy (%)	rank
0.001	88.35	1.0
0.01	88.35	1.0
1.0	88.35	1.0
0.1	88.35	1.0
0.01	88.13	5.0
0.001	88.13	5.0
0.1	88.13	5.0
1.0	88.13	5.0

6. Discussion on Breast Cancer dataset:

On evaluating different classification algorithms on the Breast Cancer dataset, we observe notable differences in performance that stem largely from the dataset's characteristics and the assumptions made by each model. The Breast Cancer dataset contains 569 samples with 30 continuous numerical features and 2 distinct classes representing malignant and benign tumors. Due to its relatively clean structure and well-separated classes, it is a common benchmark for binary classification tasks, particularly in medical diagnostics.

- The Decision Tree classifier performed well, achieving a test accuracy of 96.49% with an optimal parameter configuration including max_depth=3, max_features=None, min_samples_leaf=1, and min_samples_split=2. The model provided balanced precision, recall, and F1-scores across both classes. Its interpretability is especially valuable in healthcare applications, where understanding the reasoning behind predictions is critical. However, the limited depth while effective in preventing overfitting may slightly reduce its ability to model subtle, complex decision boundaries in some cases.
- The Gaussian Naive Bayes (GaussianNB) model emerged as the most effective, with a test accuracy of 97.37% using var_smoothing=1e-09. It leveraged the assumption that features follow a Gaussian distribution, a reasonable assumption for the dataset’s continuous features. Its performance was particularly strong due to its simplicity, low computational cost, and suitability for small-to-moderate-sized, well-structured datasets. GaussianNB achieved high class-wise precision and recall, particularly excelling in correctly classifying malignant cases while maintaining near-perfect scores for benign tumors.
- In contrast, the Bernoulli Naive Bayes (BernoulliNB) model performed less effectively, with an accuracy of only 89.47% and tuned parameters alpha=0.001, binarize=0.05, and fit_prior=True. Designed primarily for binary feature inputs, BernoulliNB is not well-suited for continuous data like that in the Breast Cancer dataset. Even with appropriate binarization, it struggled to capture the nuanced differences in the features, leading to misclassifications, especially in borderline malignant cases.
- The Multinomial Naive Bayes (MultinomialNB) model offered moderate performance, achieving a test accuracy of 93.86% with parameters alpha=0.001 and fit_prior=True. Although it outperformed BernoulliNB, it remained behind GaussianNB and Decision Tree. This is expected, as MultinomialNB assumes discrete count-based features (such as word frequencies), which misaligns with the continuous nature of the dataset’s attributes. While it handled benign cases well, it showed slightly weaker recall and precision for malignant ones.

In conclusion, GaussianNB proved to be the most effective model for the Breast Cancer dataset, thanks to its compatibility with continuous data and minimal training complexity. Decision Trees also perform robustly and offer the added benefit of interpretability. In contrast, both BernoulliNB and MultinomialNB underperformed due to their assumptions about input feature types, which do not align well with the dataset's structure. This analysis reinforces the importance of selecting models that align with the nature and distribution of the data.

7. Final conclusion for both datasets

On evaluating different classification algorithms on the Iris and Breast Cancer datasets, we observe notable differences in performance driven largely by the datasets' characteristics and each model's underlying assumptions. The Iris dataset contains 150 samples with 4 continuous numerical features and 3 distinct classes representing species of iris flowers. It is balanced, low-dimensional, and has well-separated clusters, making it a classic benchmark for multi-class classification tasks. The Breast Cancer dataset contains 569 samples with 30 continuous numerical features and 2 classes representing malignant and benign tumors. It is moderately balanced, higher in dimensionality, and serves as a benchmark for binary classification in medical diagnostics.

In terms of model performance, the Iris dataset allowed both the Decision Tree and Gaussian Naive Bayes to achieve near-perfect accuracy, benefiting from the dataset's simplicity and clear separation between classes. The Breast Cancer dataset showed a similar trend, with Gaussian Naive Bayes achieving the highest accuracy at 97.37% (var_smoothing=1e-09) and the Decision Tree close behind at 96.49% (max_depth=3, max_features=None, min_samples_leaf=1, min_samples_split=2). In both datasets, Bernoulli Naive Bayes performed the weakest—scoring poorly on Iris and only 89.47% on Breast Cancer—due to its binary feature assumption, which is incompatible with continuous data. Multinomial Naive Bayes delivered moderate results in both cases (around 93–94%), performing slightly better on Iris than Breast Cancer, but remained behind GaussianNB and Decision Trees because it is more suited to discrete count-based features.

Overall, Gaussian Naive Bayes consistently emerged as the most accurate model for both datasets, particularly excelling with continuous, normally distributed features. Decision Trees also performed strongly, offering competitive accuracy with the added benefit of interpretability, which is particularly valuable in sensitive domains like healthcare. The underperformance of BernoulliNB and MultinomialNB across both datasets reinforces the importance of aligning a model’s assumptions with the structure and distribution of the data.