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Problem 1

In [ ]:
```
import numpy as np
import pandas as pd
from pathlib import Path

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis, Quadra
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classificatior
```

```
/opt/anaconda3/lib/python3.9/site-packages/scipy/__init__.py:146: UserWarnin
g: A NumPy version >=1.16.5 and <1.23.0 is required for this version of SciP
y (detected version 1.26.4
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

In [2]:
```
data_path = Path("./wine/wine.data")

columns = [
    "Class",
    "Alcohol",
    "Malic acid",
    "Ash",
    "Alcalinity of ash",
    "Magnesium",
    "Total phenols",
    "Flavanoids",
    "Nonflavanoid phenols",
    "Proanthocyanins",
    "Color intensity",
    "Hue",
    "OD280/OD315 of diluted wines",
    "Proline",
]

df = pd.read_csv(data_path, header=None, names=columns)
df.head()
```

Out[2]:

	Class	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavan phen
0	1	14.23	1.71	2.43	15.6	127	2.80	3.06	0
1	1	13.20	1.78	2.14	11.2	100	2.65	2.76	0
2	1	13.16	2.36	2.67	18.6	101	2.80	3.24	0
3	1	14.37	1.95	2.50	16.8	113	3.85	3.49	0
4	1	13.24	2.59	2.87	21.0	118	2.80	2.69	0

In [3]:
```
X = df.drop(columns=["Class"])
y = df["Class"]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.30, random_state=598, stratify=y
)
```

Part A:

In [9]:
```
lda = LinearDiscriminantAnalysis()
qda = QuadraticDiscriminantAnalysis()
mlog = LogisticRegression(
    multi_class="multinomial", solver="lbfgs", max_iter=5000, random_state=5
)

lda.fit(X_train, y_train)
qda.fit(X_train, y_train)
mlog.fit(X_train, y_train)

models = {
    "LDA": lda,
    "QDA": qda,
    "Multinomial Logistic": mlog
}
```

Part B:

In [10]:
```
rows = []
for name, model in models.items():
    y_pred_tr = model.predict(X_train)
    y_pred_te = model.predict(X_test)
    rows.append({
        "Model": name,
        "Train Accuracy": accuracy_score(y_train, y_pred_tr),
        "Test Accuracy": accuracy_score(y_test, y_pred_te)
    })
```

```
acc_df = pd.DataFrame(rows)
acc_df
```

Out[10]:

	Model	Train Accuracy	Test Accuracy
0	LDA	1.0	1.000000
1	QDA	1.0	1.000000
2	Multinomial Logistic	1.0	0.962963

In [7]:

```
labels = [1, 2, 3]

for name, model in models.items():
    print(f"\n=== {name} ===")
    cm_train = pd.DataFrame(
        confusion_matrix(y_train, model.predict(X_train), labels=labels),
        index=[f"True_{c}" for c in labels],
        columns=[f"Pred_{c}" for c in labels]
    )
    print("\nTrain:")
    display(cm_train)

    cm_test = pd.DataFrame(
        confusion_matrix(y_test, model.predict(X_test), labels=labels),
        index=[f"True_{c}" for c in labels],
        columns=[f"Pred_{c}" for c in labels]
    )
    print("Test:")
    display(cm_test)
```

```
=== LDA ===

Train:
```

	Pred_1	Pred_2	Pred_3
True_1	41	0	0
True_2	0	50	0
True_3	0	0	33

```
Test:
```

	Pred_1	Pred_2	Pred_3
True_1	18	0	0
True_2	0	21	0
True_3	0	0	15

```
=== QDA ===

Train:
```

	Pred_1	Pred_2	Pred_3
True_1	41	0	0
True_2	0	50	0
True_3	0	0	33

```
Test:
```

	Pred_1	Pred_2	Pred_3
True_1	18	0	0
True_2	0	21	0
True_3	0	0	15

```
=== Multinomial Logistic ===

Train:
```

	Pred_1	Pred_2	Pred_3
True_1	40	1	0
True_2	0	50	0
True_3	0	0	33

```
Test:
```

	Pred_1	Pred_2	Pred_3
True_1	17	1	0
True_2	0	20	1
True_3	0	0	15

Part C:

All three models LDA, QDA, and Multinomial Logistic Regression performed extremely well on the Wine dataset. LDA and QDA both achieved 100% accuracy on the training and testing data, while the logistic regression model reached 100% on training and about 96% on testing. This shows that the dataset is highly separable, with clear differences between the three wine classes. The misclassifications from logistic regression occurred between Class 1 and Class 2, while Class 3 was predicted perfectly by all models. Overall, LDA and QDA performed best with no misclassifications and better accuracy.

Problem 2

In [12]:
```
import pandas as pd
import numpy as np
from ucimlrepo import fetch_ucirepo
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatri
```

In [13]:
```
#code from the UCI Data Repository: https://doi.org/10.24432/C5MG6K
pen_based_recognition_of_handwritten_digits = fetch_ucirepo(id=81)
X = pen_based_recognition_of_handwritten_digits.data.features
y = pen_based_recognition_of_handwritten_digits.data.targets

#split into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, rar
```

Parts (a), (b), (c) - Fit Models

In [14]:
```
#fit SVM, decision tree classifier, AdaBoost, Gradient Boosting
svm_model = SVC(kernel='rbf', random_state=598)
svm_model.fit(X_train, y_train)

dt_model = DecisionTreeClassifier(random_state=598)
dt_model.fit(X_train, y_train)

ab_model = AdaBoostClassifier(random_state=598)
ab_model.fit(X_train, y_train)

gb_model = GradientBoostingClassifier(random_state=598)
gb_model.fit(X_train, y_train)
```

```
/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/validation.py:993:
DataConversionWarning: A column-vector y was passed when a 1d array was expe
cted. Please change the shape of y to (n_samples, ), for example using ravel
().
  y = column_or_1d(y, warn=True)
/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/validation.py:993:
DataConversionWarning: A column-vector y was passed when a 1d array was expe
cted. Please change the shape of y to (n_samples, ), for example using ravel
().
  y = column_or_1d(y, warn=True)
/opt/anaconda3/lib/python3.9/site-packages/sklearn/ensemble/_gb.py:494: Data
ConversionWarning: A column-vector y was passed when a 1d array was expecte
d. Please change the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

Out[14]:
```
GradientBoostingClassifier(random_state=598)
```

Part (d) - Train and Test Accuracies

In [15]:
```
#Accuracy for all classifiers in both training and testing data
models = [('Gaussian SVM', svm_model), ('Decision Tree', dt_model), ('AdaBoo

results = []
confusion_matrix_results = []

for name, model in models:
    #training data
    y_pred_train = model.predict(X_train)
    train_accuracy = model.score(X_train, y_train)

    #testing data
    y_pred_test = model.predict(X_test)
    test_accuracy = model.score(X_test, y_test)
    results.append({"Model": name, "Train Accuracy": train_accuracy, "Test A

    #get confusion matrix for test data for part e
    confusion_matrix_test = confusion_matrix(y_test, y_pred_test)
    confusion_matrix_results.append((name, confusion_matrix_test))

results_df = pd.DataFrame(results)
print(results_df)
```

```
              Model  Train Accuracy  Test Accuracy
0       Gaussian SVM        0.995191       0.994239
1      Decision Tree        1.000000       0.958156
2           AdaBoost        0.357681       0.353244
3  Gradient Boosting        1.000000       0.984536
```

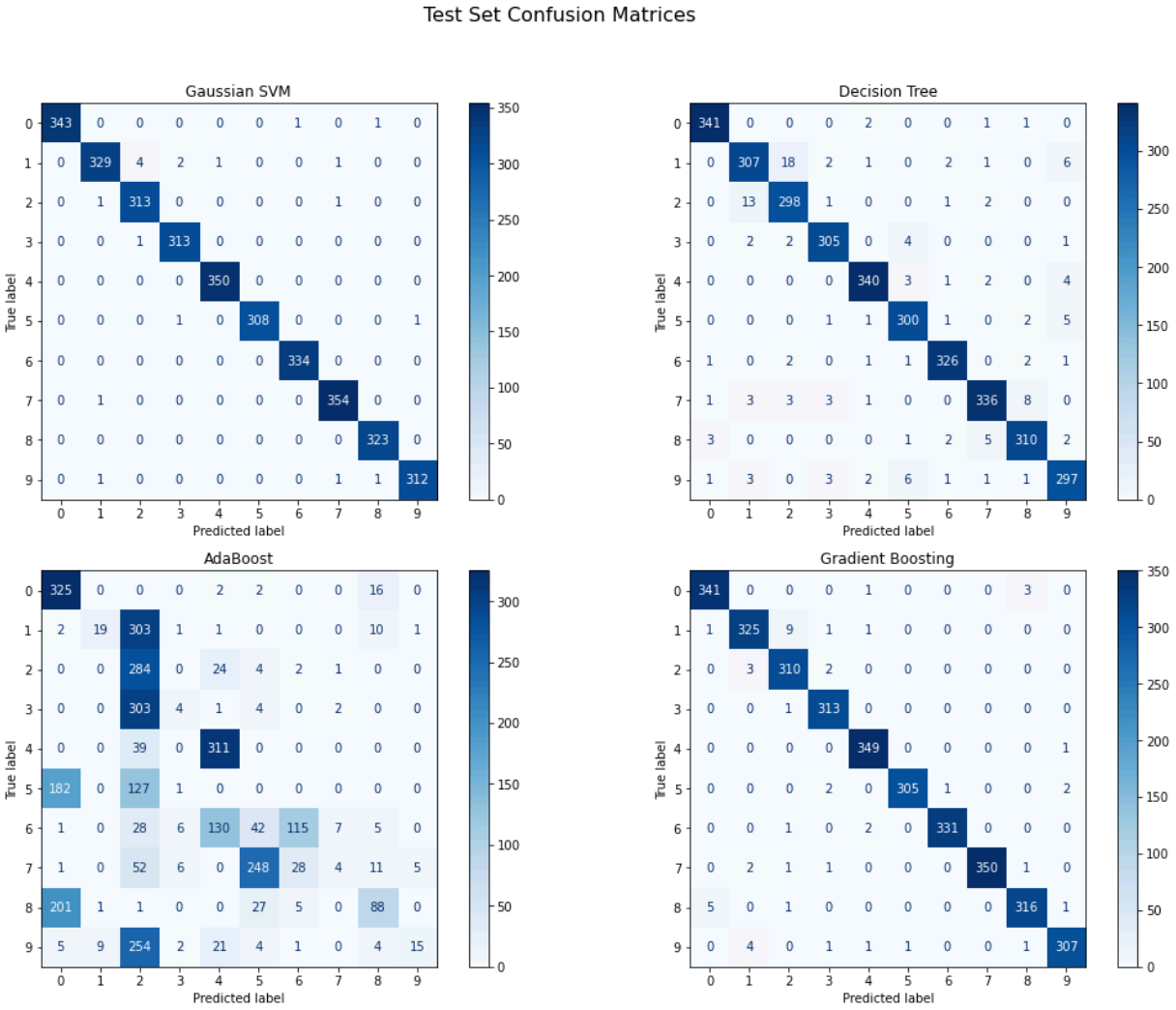
Training and testing accuracies

Model	Train Accuracy	Test Accuracy
Gaussian SVM	0.995191	0.994239
Decision Tree	1.000000	0.958156
AdaBoost	0.619054	0.620376
Gradient Boosting	1.000000	0.984536

Part (e) - Confusion Matrices

In [16]:
```
#Show confusion matrices for test predictions
labels = np.unique(y)
labels.sort()
target_names = [str(label) for label in labels]

fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(15, 12))
fig.suptitle('Test Set Confusion Matrices', fontsize=16)
axes_flat = axes.flatten()

for (name, cm), ax in zip(confusion_matrix_results, axes_flat):
```

```
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=target
    disp.plot(ax=ax, cmap='Blues')
    ax.set_title(f'{name}')

num_plots = len(confusion_matrix_results)
for i in range(num_plots, len(axes_flat)):
    axes_flat[i].axis('off')

plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```



Part (f) - Comments on Results

Overall, the Gaussian SVM and Gradient Boosting models performed the best, with testing accuracies of 0.994239 and 0.984536, respectively. The Decision Tree was also very good but made more errors, acheiving a testing accuracy of 0.958156. The AdaBoost model did not perform well with a testing accuracy of 0.620376, showing a lot of confusion and an inability to model the data effectively.

Analysis of Individual Confusion Matrices

- SVM with a Guassian Kernel (accuracy 0.994239): This was the best performer on the data. The diagonal is nearly perfect, meaning almost all digits were classified correctly. The errors are minimal and spread out.
- Gradient Boosting (accuracy 0.984536): This model was the second best, performing almost as well as the SVM, with a very clean diagonal. The most significant errors were misclassifying 9 true '1's as '2's and misclassifying 5 true '8's as '0's, but these are very small errors.
- Decision Tree (accuracy 0.958156): This model was the third best, and had a small, but significant decrease in accuracy from the best two models. While it got most predictions right, the number of errors is much higher. There seems to be a strong confusion between '1' and '2' (18 true '1's were called '2's, and 13 true '2's were called '1's). There were also other errors, which are visible in the confusion matrix.
- AdaBoost (accuracy 0.620376): This model performed the worst and didn't model the data properly. The confusion matrix shows a lot of errors, and the diagonal values for a lot of classes are very low. For example:
  - It was very bad at classifying '8's, with only 67 correct classifications and 171 true '8's being misclassified as '0'.
  - It was very bad at identifying '3', with only 39 correct classifications, 163 true '3's misclassified as '5', and 111 true '3's misclassified as '1'.
  - It also heavily confused '2's and '9's with '1's.

Which are the digits that seem to be most commonly confused?

Based on the confusion matrices, the most common confusions are:

- Misclassifying '1' as '2': This was the biggest problem for the Decision Tree and a massive issue for AdaBoost. Even the SVM and Gradient Boosting had their largest errors on '1' and '2'.
- Misclassifying '9' as '1': We saw this in every model, though with small errors in all models other than AdaBoost.
- Misclassifying '8' as '0': We saw this in every model other than SVM, with Adaboost having the largest error across all models at 171 misclassifiactions on this pair.
- Misclassifying '2' as '1': We saw this in every model but the SVM.
- Misclassifying '3' as '5': We saw this in AdaBoost (163 errors) and Decision Tree (4 errors).

Did you have any overfitting issues with any of the approaches?

The accuracy table clearly identifies which models overfit the data.

- Gaussian SVM: No. This model is the best example of a good fit. The training accuracy (0.995191) and testing accuracy (0.994239) are pretty much the same (difference of 0.000952). This drop of 0.1% is negligible, meaning it learned the patterns without memorizing the noise, which is why it was the best performer on the testing data.
- Gradient Boosting: Yes, but it was small. The training accuracy (1.000000) and testing accuracy (0.984536) are close (difference of 0.015464). This drop of 1.5% is technically overfitting, the drop is much smaller, and the model was still very accurate and generalizable.
- Decision Tree: Yes. This is the first example where we can see proper overfitting. The training accuracy (1.000000) and testing accuracy (0.958156) are close (difference of 0.041844). This drop of 4.2% shows it memorized the training data and didn't generalize perfectly to new data, even though it is relatively small.
- AdaBoost: No. This model was actually underfitting. We know this because the model performed poorly on both the training data (accuracy 0.619054) and the testing data (accuracy 0.620376). Though the difference between the two accuracies is small, this is underfitting because the accuracy is low overall, meaning model was suitable to capture the patterns in the data.