Random Forest

Dataset Description:

Use the Glass dataset and apply the Random forest model.

1. Exploratory Data Analysis (EDA):

Perform exploratory data analysis to understand the structure of the dataset. Check for missing values, outliers, inconsistencies in the data.

Answer:

```
(.venv) PS D:\python apps> & "D:/python apps/my-streamlit-
app/.venv/Scripts/python.exe" "d:/python apps/random
forest/eda_glass_randomforest.py"
Shape of dataset: (214, 10)

--- Dataset Info ---
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 214 entries, 0 to 213
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   RI      214 non-null    float64
 1   Na      214 non-null    float64
 2   Mg      214 non-null    float64
 3   Al      214 non-null    float64
 4   Si      214 non-null    float64
 5   K       214 non-null    float64
 6   Ca      214 non-null    float64
 7   Ba      214 non-null    float64
 8   Fe      214 non-null    float64
 9   Type    214 non-null    int64
dtypes: float64(9), int64(1)
memory usage: 16.8 KB
None

--- Missing Values ---
RI      0
Na      0
Mg      0
Al      0
Si      0
K       0
Ca      0
Ba      0
Fe      0
Type    0
dtype: int64
```

Duplicate rows: 1

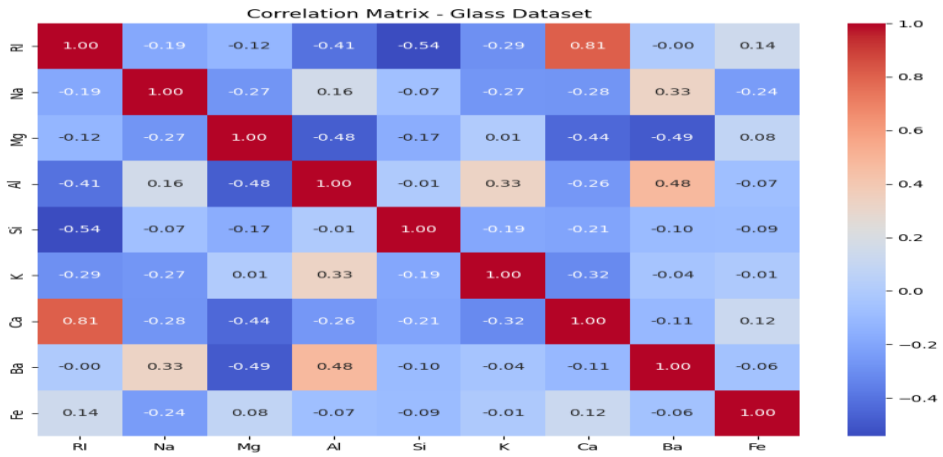
--- Summary Statistics ---

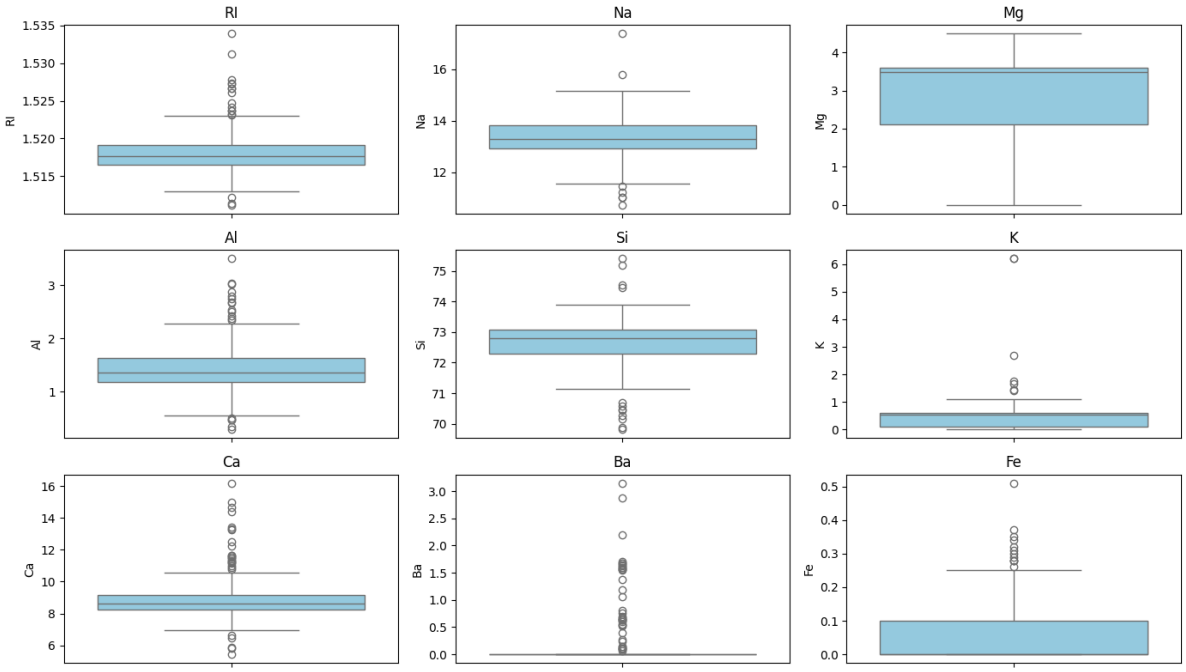
	count	mean	...	75%	max
RI	214.0	1.518365	...	1.519157	1.53393
Na	214.0	13.407850	...	13.825000	17.38000
Mg	214.0	2.684533	...	3.600000	4.49000
Al	214.0	1.444907	...	1.630000	3.50000
Si	214.0	72.650935	...	73.087500	75.41000
K	214.0	0.497056	...	0.610000	6.21000
Ca	214.0	8.956963	...	9.172500	16.19000
Ba	214.0	0.175047	...	0.000000	3.15000
Fe	214.0	0.057009	...	0.100000	0.51000
Type	214.0	2.780374	...	3.000000	7.00000

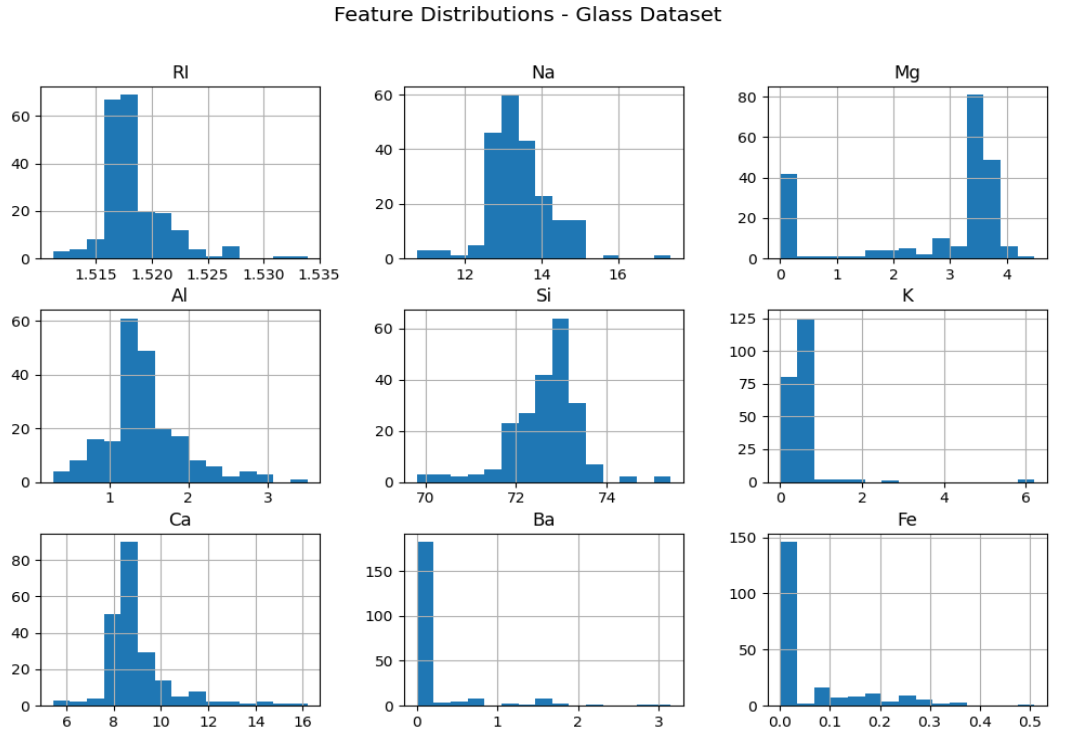
[10 rows x 8 columns]

--- Target Value Counts (Type) ---
Type
2 76
1 70
7 29
3 17
5 13
6 9
Name: count, dtype: int64

EDA completed successfully.
Plots saved in: D:\DATA SCIENCE\ASSIGNMENTS\14 random forest\Random Forest
Files created:
- histograms.png
- boxplots.png
- correlation_matrix.png




RI
Na
Mg
Al
Si
K
Ca
Ba
Fe


Feature Distributions - Glass Dataset
RI
Na
Mg
Al
Si
K
Ca
Ba
Fe

2: Data Visualization:

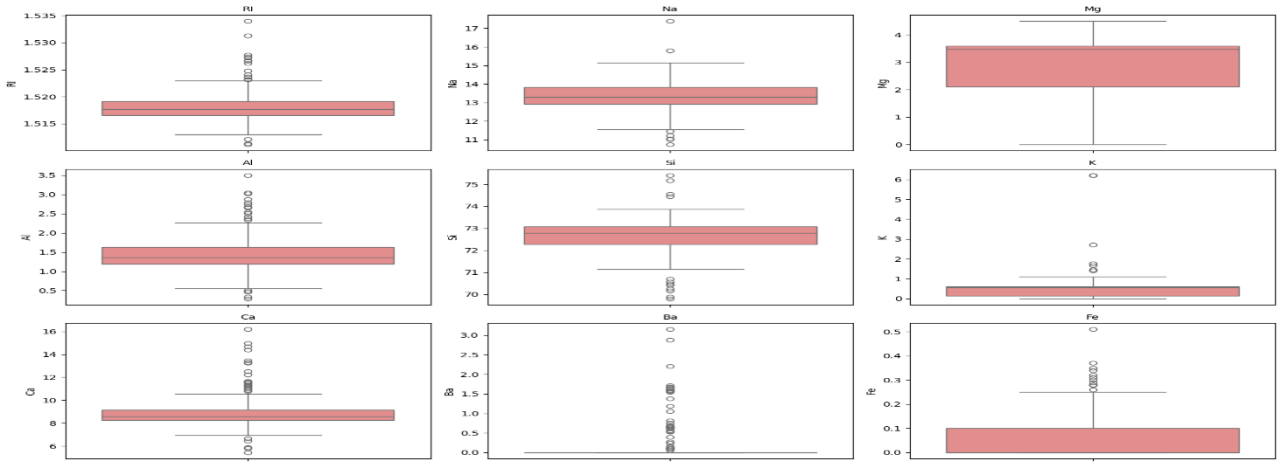
Create visualizations such as histograms, box plots, or pair plots to visualize the distributions and relationships between features.
Analyze any patterns or correlations observed in the data.

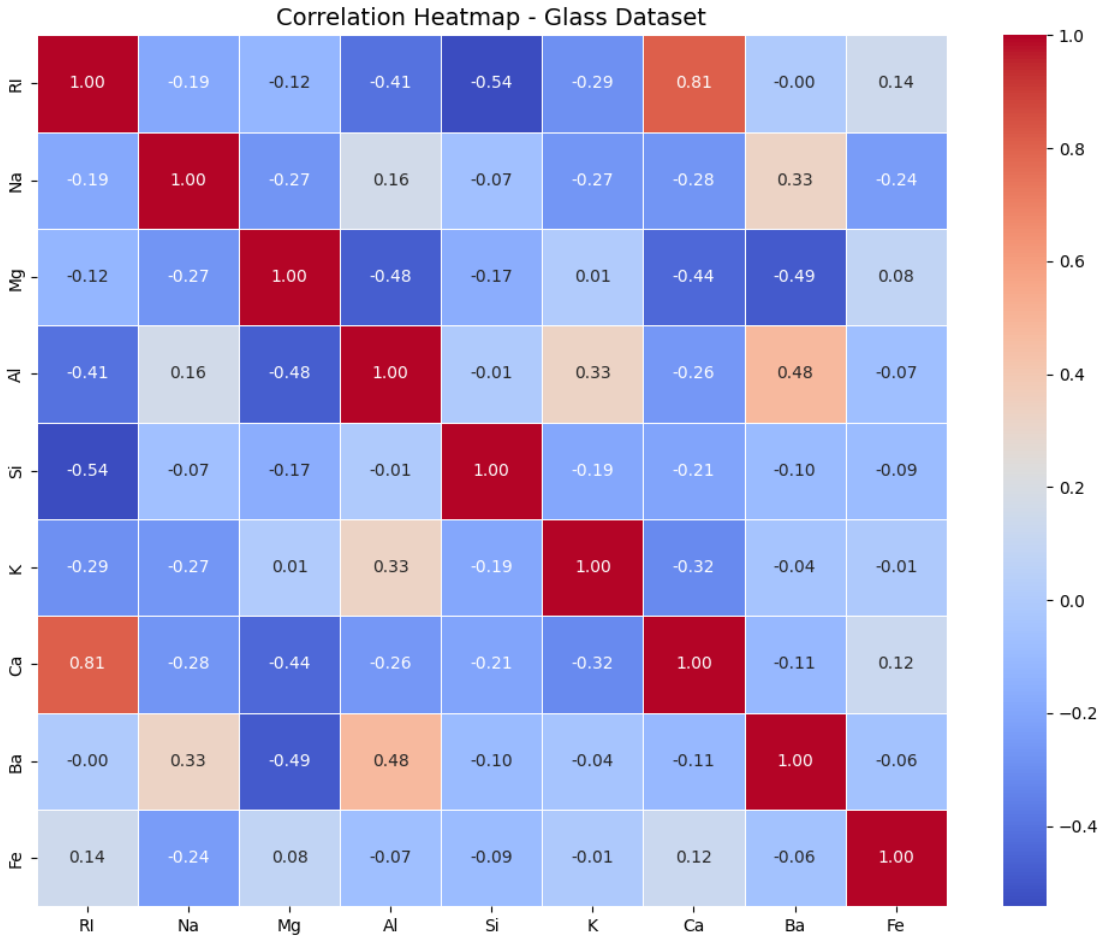
🧠 What this does:

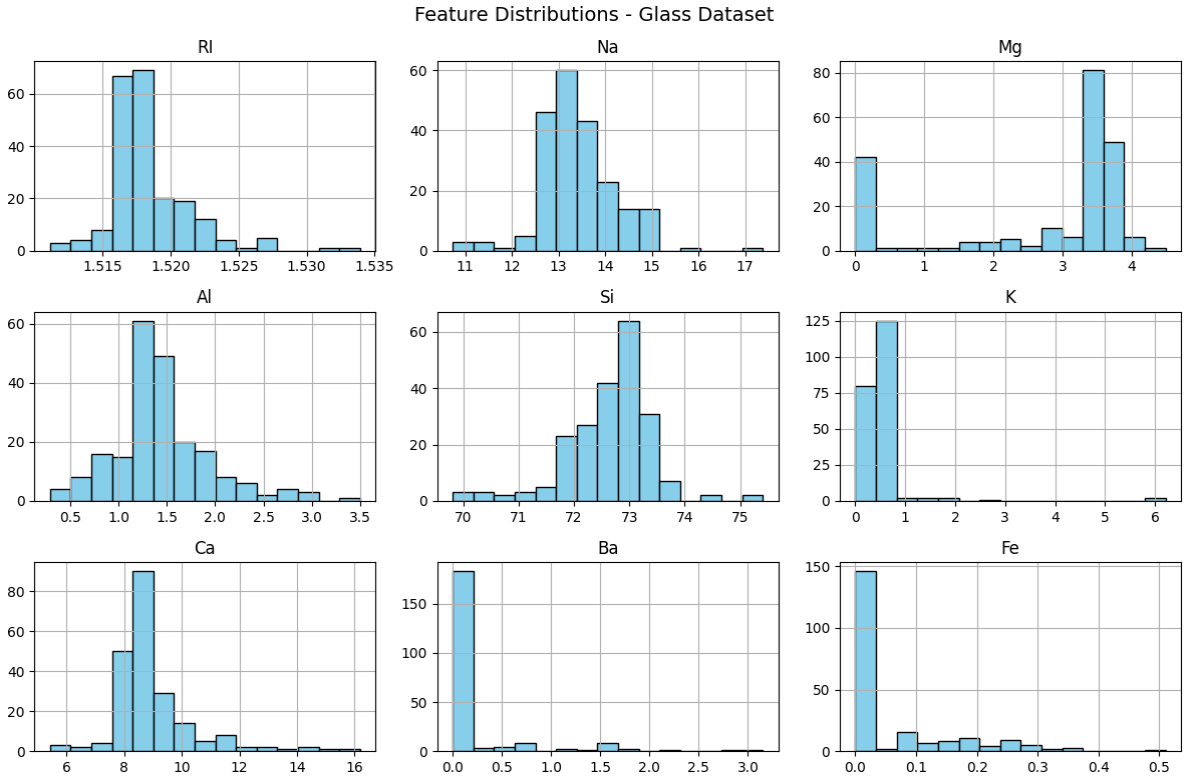
- Reads the **Glass dataset**.
- Generates:
  - `histograms.png` → Distribution of each feature
  - `boxplots.png` → Outliers and range visualization
  - `pairplot.png` → Relationship between features and glass type
  - `correlation_heatmap.png` → Correlation between numerical features
- Saves all visualizations into folder automatically.
- Prints **interpretation insights**

🧩 Summary of Key Patterns

- **Aluminium (Al)** and **Magnesium (Mg)** show strong inverse correlation — glasses richer in Mg tend to have less Al.
- **Refractive Index (RI)** increases with **Calcium (Ca)** content.
- **Potassium (K)**, **Barium (Ba)**, and **Iron (Fe)** are sparse (many zeros) — might be less informative.
- Some glass types form **distinct clusters** in the pair plot, especially for combinations like `(Al, Mg)` and `(RI, Ca)`.




Correlation Heatmap - Glass Dataset
RI
Na
Mg
Al
Si
K
Ca
Ba
Fe
1.00 -0.19 -0.12 -0.41 -0.54 -0.29 0.81 -0.00 0.14
-0.19 1.00 -0.27 0.16 -0.07 -0.27 -0.28 0.33 -0.24
-0.12 -0.27 1.00 -0.48 -0.17 0.01 -0.44 -0.49 0.08
-0.41 0.16 -0.48 1.00 -0.01 0.33 -0.26 0.48 -0.07
-0.54 -0.07 -0.17 -0.01 1.00 -0.19 -0.21 -0.10 -0.09
-0.29 -0.27 0.01 0.33 -0.19 1.00 -0.32 -0.04 -0.01
0.81 -0.28 -0.44 -0.26 -0.21 -0.32 1.00 -0.11 0.12
-0.00 0.33 -0.49 0.48 -0.10 -0.04 -0.11 1.00 -0.06
0.14 -0.24 0.08 -0.07 -0.09 -0.01 0.12 -0.06 1.00
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4


Feature Distributions - Glass Dataset
RI
Na
Mg
Al
Si
K
Ca
Ba
Fe


RI
Na
Mg
Al
Si
K
Ca
Ba
Fe
Type
1
2
3
5
6
7

(.venv) PS D:\python apps> & "D:/python apps/my-streamlit-app/.venv/Scripts/python.exe" "d:/python apps/random forest/data_visualization_glass.py"
Shape of dataset: (214, 10)
Columns: ['RI', 'Na', 'Mg', 'Al', 'Si', 'K', 'Ca', 'Ba', 'Fe', 'Type']

Glass Types: [1 2 3 5 6 7]

✅ Data Visualization Completed.
Visual files saved in: D:\DATA SCIENCE\ASSIGNMENTS\14 random forest\Random Forest
- histograms.png
- boxplots.png
- pairplot.png
- correlation_heatmap.png

--- ANALYSIS INSIGHTS ---
1. Some features like 'K', 'Ba', and 'Fe' have strong skew (many zeros).
2. 'RI', 'Na', 'Mg', and 'Ca' show wider variation across glass types.
3. Pairplot reveals partial separation between certain glass types using 'Mg' and 'Al'.
4. Correlation heatmap shows:
  - 'Al' and 'Mg' are negatively correlated.
  - 'RI' and 'Si' show mild inverse relationship.
  - 'Ca' correlates positively with 'RI' and negatively with 'Al'.

These patterns will help Random Forest identify which elements drive glass classification.

3: Data Preprocessing

1. Check for missing values in the dataset and decide on a strategy for handling them.Implement the chosen strategy (e.g., imputation or removal) and explain your reasoning.
2. If there are categorical variables, apply encoding techniques like one-hot encoding to convert them into numerical format.
3. Apply feature scaling techniques such as standardization or normalization to ensure that all features are on a similar scale. Handling the imbalance data.

Answer:

Explanation of Each Step

1️⃣ Missing Values
- The Glass dataset rarely has nulls, but this script still checks and fills them with median imputation (robust to outliers).
- Reasoning: Median is better than mean for skewed data, such as chemical concentrations.

2️⃣ Categorical Encoding
- The dataset has no categorical variables — all features are numeric.
- If future datasets have non-numeric columns, this script can automatically one-hot encode them.

3️⃣ **Feature Scaling**

- Standardization is applied using StandardScaler:
  - Transforms each feature to have mean = 0 and std = 1.
  - Though Random Forests don't *require* scaling, it helps keep preprocessing pipeline consistent (and avoids skewed feature influence in visualizations or distance-based metrics).

4️⃣ **Handling Imbalance**

- The Type variable (target) is multi-class and imbalanced — some glass types have fewer samples.
- SMOTE (Synthetic Minority Oversampling Technique) is used to generate synthetic samples for minority classes.
- After SMOTE, all classes will have equal representation, improving Random Forest training stability.

💾 **Output Files Saved in Folder**

- glass_processed.csv → Preprocessed dataset (scaled + balanced).

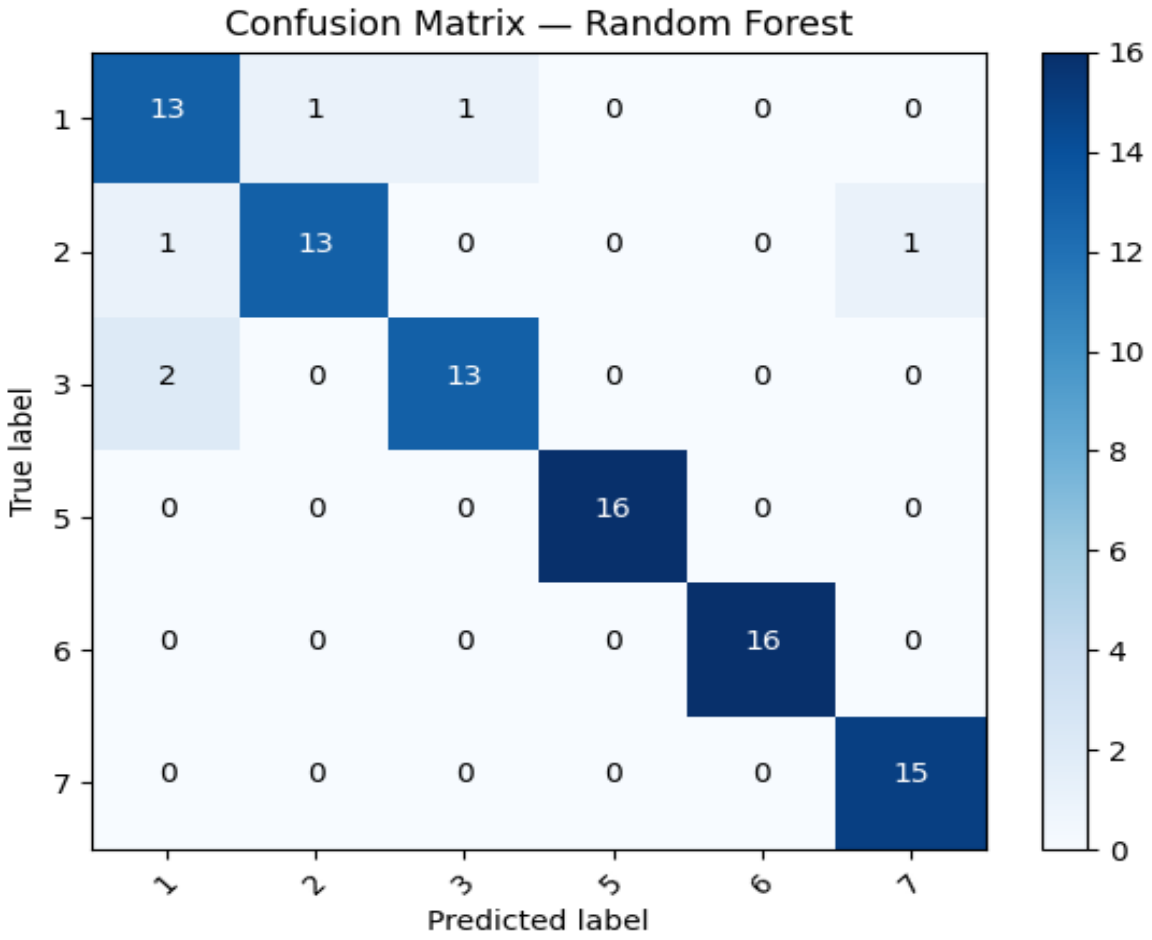
```
(.venv) PS D:\python apps> & "D:/python apps/my-streamlit-app/.venv/Scripts/python.exe" "d:/python apps/random forest/preprocessing_glass_randomforest.py"
✅ Dataset loaded successfully.
Shape: (214, 10)

--- Missing Values Check ---
RI      0
Na      0
Mg      0
Al      0
Si      0
K       0
Ca      0
Ba      0
Fe      0
Type    0
dtype: int64

No missing values found — no imputation needed.

No categorical columns — encoding not required.

Feature scaling (Standardization) applied successfully.
Mean of scaled features (approx):
 RI   -0.0
Na    0.0
Mg   -0.0
Al   -0.0
Si    0.0
K     0.0
```

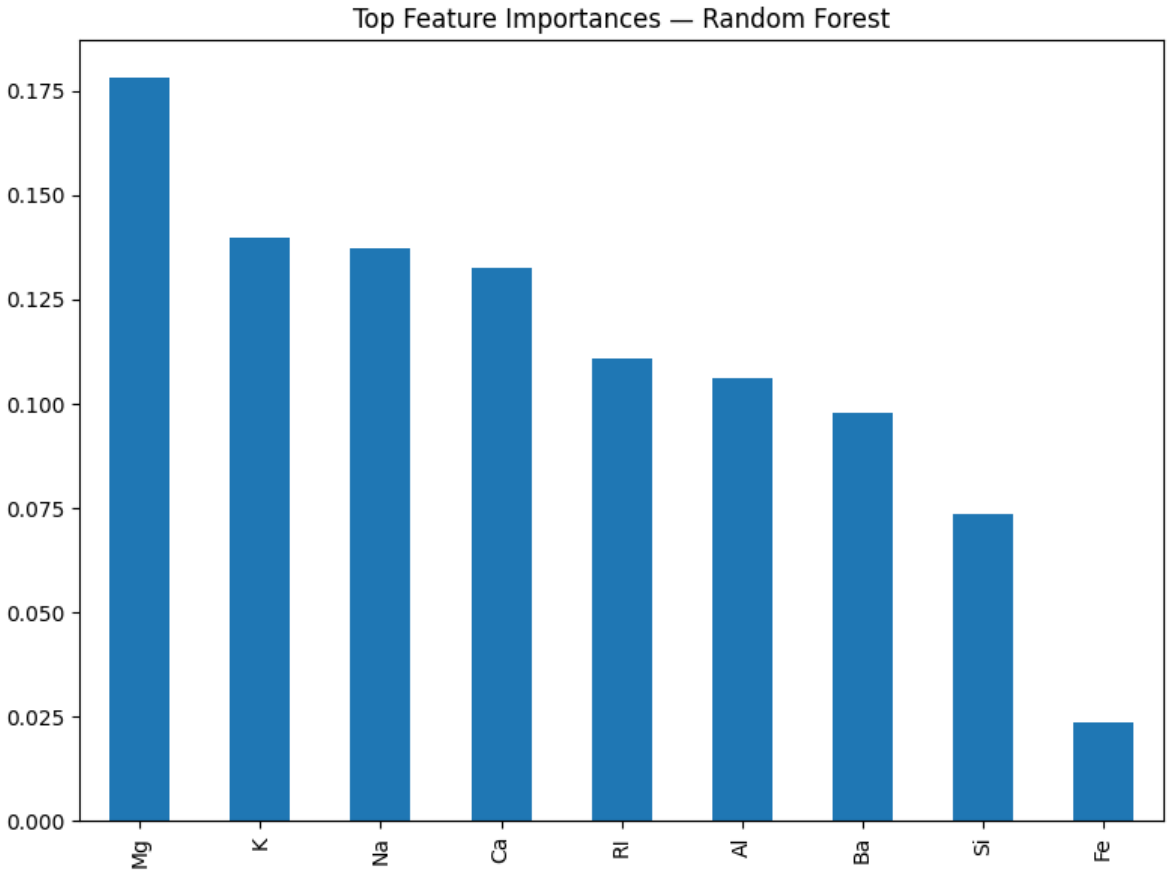
```
Ca   -0.0
Ba   -0.0
Fe   -0.0
dtype: float64
Std dev of scaled features (approx):
 RI    1.002
Na    1.002
Mg    1.002
Al    1.002
Si    1.002
K     1.002
Ca    1.002
Ba    1.002
Fe    1.002
dtype: float64

--- Target Distribution Before Balancing ---
Type
2    76
1    70
7    29
3    17
5    13
6     9
Name: count, dtype: int64

SMOTE applied successfully.
--- Target Distribution After SMOTE Balancing ---
Type
1    76
2    76
3    76
5    76
6    76
7    76
Name: count, dtype: int64

✅ Data Preprocessing Completed Successfully.
Processed file saved as: D:\DATA SCIENCE\ASSIGNMENTS\14 random forest\Random Forest\glass_processed.csv
Final shape: (456, 10)
```

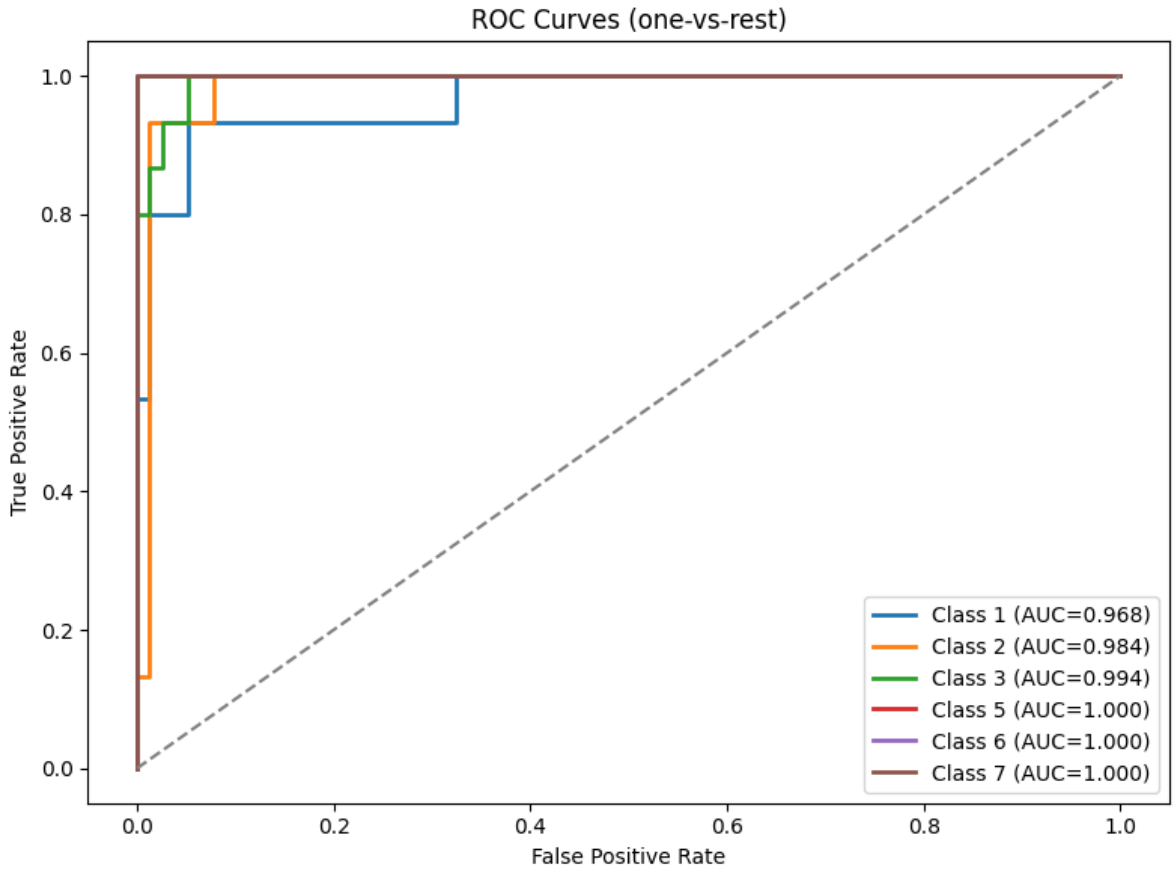
4: Random Forest Model Implementation
1. Divide the data into train and test split.
2. Implement a Random Forest classifier using Python and a machine learning library like scikit-learn.
3. Train the model on the train dataset. Evaluate the performance on test data using metrics like accuracy, precision, recall, and F1-score.

Answer:

```
(.venv) PS D:\python apps> & "D:/python apps/my-streamlit-app/.venv/Scripts/python.exe" "d:/python apps/train_random_forest_glass.py"
Loading processed data: D:\DATA SCIENCE\ASSIGNMENTS\14 random forest\Random Forest\glass_processed.csv
Train / Test shapes: (364, 9) (92, 9)
Saved model to: D:\DATA SCIENCE\ASSIGNMENTS\14 random forest\Random Forest\random_forest_glass.pkl
Saved evaluation report to: D:\DATA SCIENCE\ASSIGNMENTS\14 random forest\Random Forest\random_forest_evaluation.txt
Saved confusion matrix to: D:\DATA SCIENCE\ASSIGNMENTS\14 random forest\Random Forest\confusion_matrix_rf.png
Saved ROC plot to: D:\DATA SCIENCE\ASSIGNMENTS\14 random forest\Random Forest\roc_curve_rf.png
Saved feature importances to: D:\DATA SCIENCE\ASSIGNMENTS\14 random forest\Random Forest\feature_importances_rf.png

=== Summary Metrics ===
Accuracy: 0.9348
Precision (macro): 0.9345
Recall (macro): 0.9333
F1 (macro): 0.9333

Classification report (per class):
              precision    recall  f1-score   support

           1       0.81      0.87      0.84        15
           2       0.93      0.87      0.90        15
           3       0.93      0.87      0.90        15
           5       1.00      1.00      1.00        16
           6       1.00      1.00      1.00        16
           7       0.94      1.00      0.97        15

    accuracy                           0.93        92
   macro avg       0.93      0.93      0.93        92
weighted avg       0.94      0.93      0.93        92

Confusion Matrix:
[[13  1  1  0  0  0]
 [ 1 13  0  0  0  1]
 [ 2  0 13  0  0  0]
 [ 0  0  0 16  0  0]
 [ 0  0  0  0 16  0]
 [ 0  0  0  0  0 15]]
```


Confusion Matrix — Random Forest
True label
Predicted label
1
2
3
5
6
7
13 1 1 0 0 0
1 13 0 0 0 1
2 0 13 0 0 0
0 0 0 16 0 0
0 0 0 0 16 0
0 0 0 0 0 15
16
14
12
10
8
6
4
2
0


Top Feature Importances — Random Forest
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
Mg
K
Na
Ca
RI
Al
Ba
Si
Fe



Quick notes & tips (because I care)

- `n_estimators=200` is a sensible default. Increase if you want smoother feature importances (slower training).
- Random Forests are robust to scaling — we still standardize for consistency with pipeline.
- If you used SMOTE previously, `glass_processed.csv` may be balanced — good. If not, RF can still handle imbalance okay, but consider class weights or resampling for marginal classes.

5: Bagging and Boosting Methods
Apply the Bagging and Boosting methods and compare the results.

Answer:

• Loads processed dataset (`glass_processed.csv`) or creates a quick processed version from `glass.xlsx` if needed.

• Splits the data (stratified 80/20).

• Trains **Bagging** (BaggingClassifier with DecisionTree base), **AdaBoost**, **Gradient Boosting**, and optionally **XGBoost** (if `xgboost` is installed).

- Evaluates each model (accuracy, precision, recall, F1 macro), computes confusion matrices, and — if possible — ROC-AUC (one-vs-rest).

- Saves models and evaluation artifacts into folder:
`D:\DATA SCIENCE\ASSIGNMENTS\14 random forest\Random Forest\`

- Produces a comparison table and a bar chart of metrics.

- baseline.
- **AdaBoost** focuses on mistakes sequentially; it can be brittle with noisy labels but fantastic for clean data.
- **GradientBoosting** builds trees to correct previous residual errors and often achieves strong accuracy with careful tuning.
- **XGBoost** (if available) is often faster and more powerful than sklearn's GradientBoosting, but it's optional.

What to look for in results

- If Bagging/RandomForest outperforms boosting → variance was a bigger issue (trees were overfitting).
- If Boosting wins → model benefits from staged focusing on hard examples (might capture subtle patterns).
- Look at **per-class** precision/recall in the reports to see which glass types are being confused (useful for assignment discussion).

(.venv) PS D:\python apps> & "D:/python apps/my-streamlit-app/.venv/Scripts/python.exe" "d:/python apps/random forest/compare_bagging_boosting_glass.py"

Loading processed data: D:\DATA SCIENCE\ASSIGNMENTS\14 random forest\Random Forest\glass_processed.csv

Train/Test shapes: (171, 9) (43, 9)

Trained BaggingClassifier

Trained AdaBoostClassifier

Trained GradientBoostingClassifier

Trained RandomForestClassifier

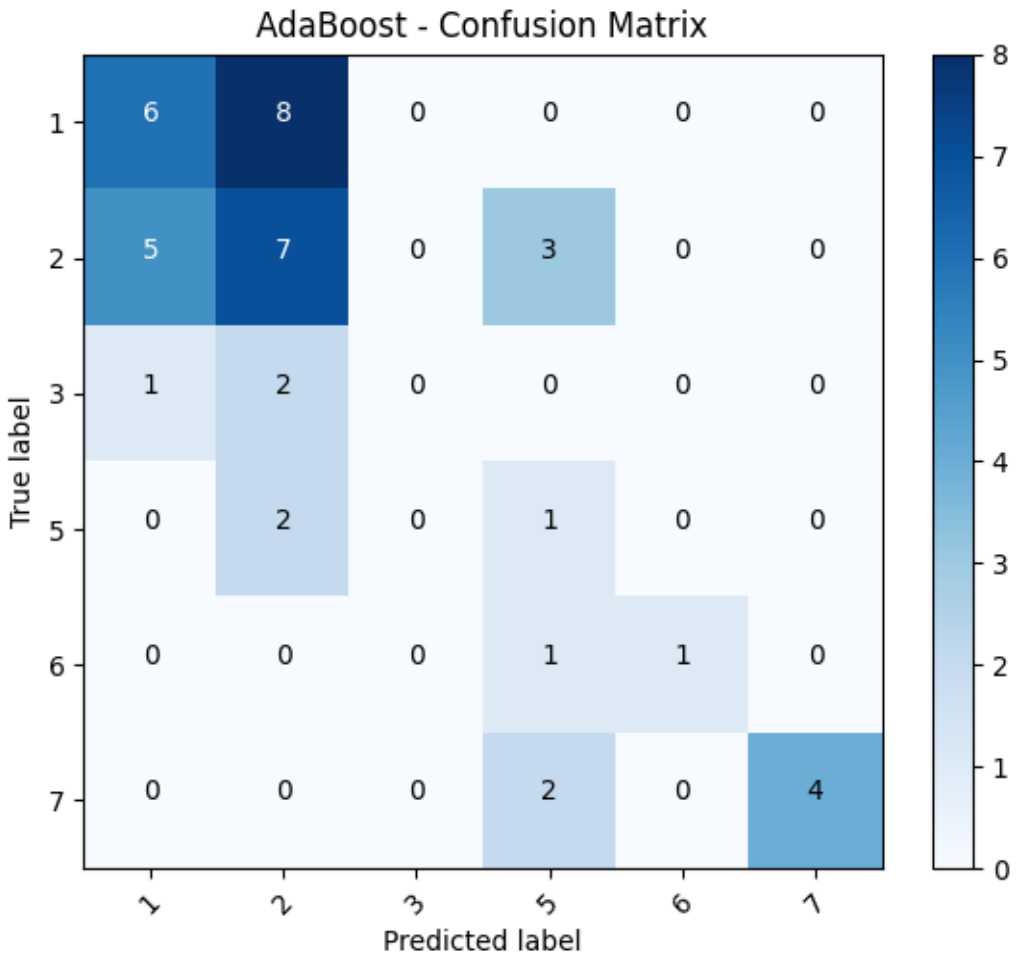
XGBoost not available or failed to train — skipping.

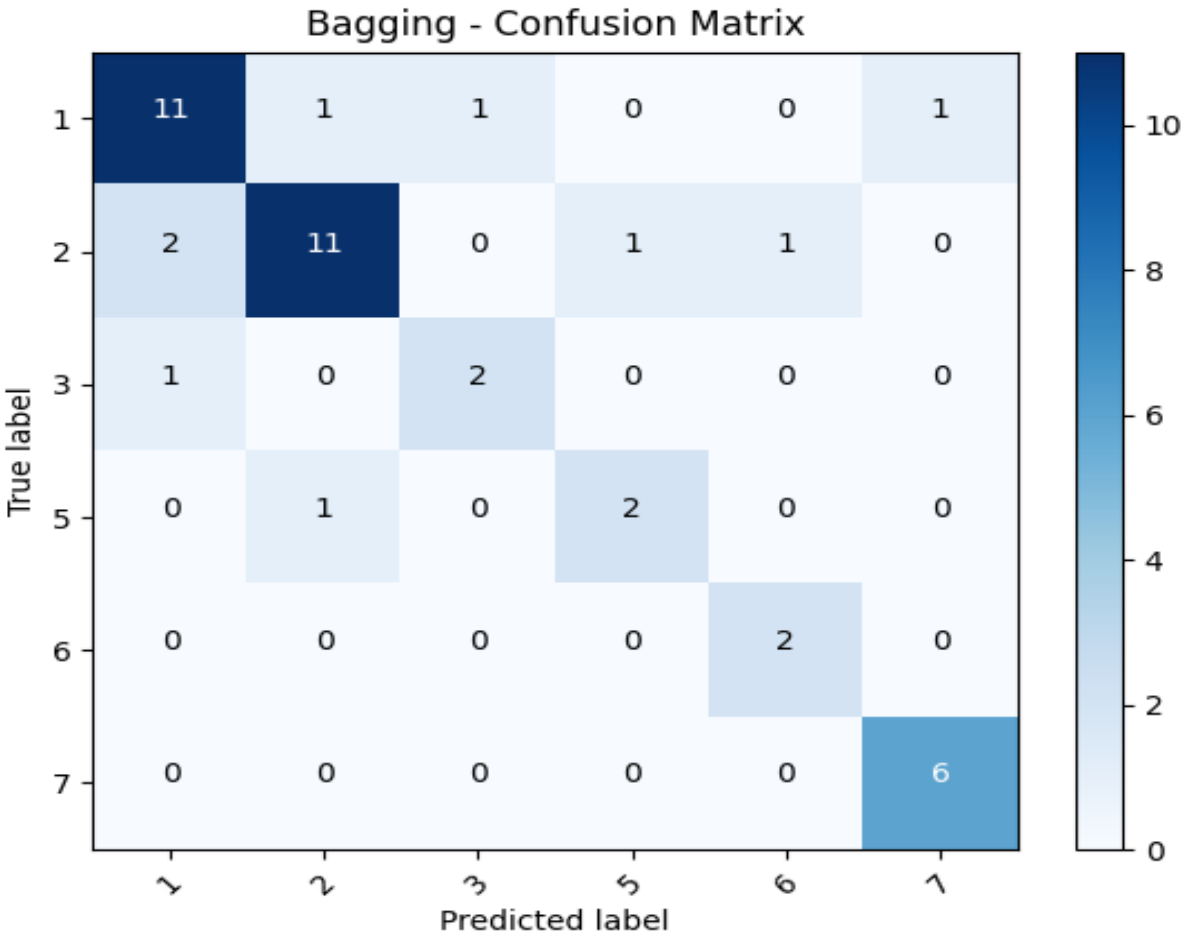
Reason: No module named 'xgboost'

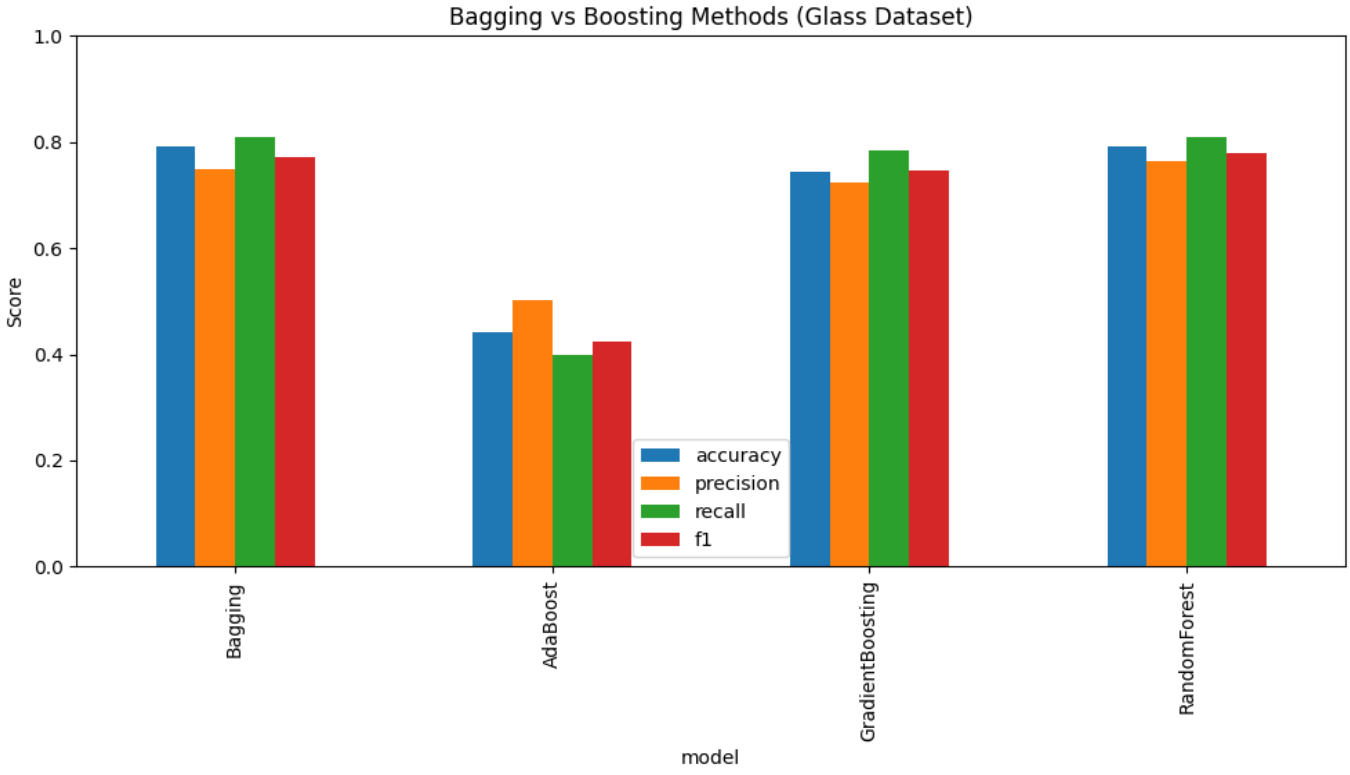
=== Ensemble Comparison Results ===

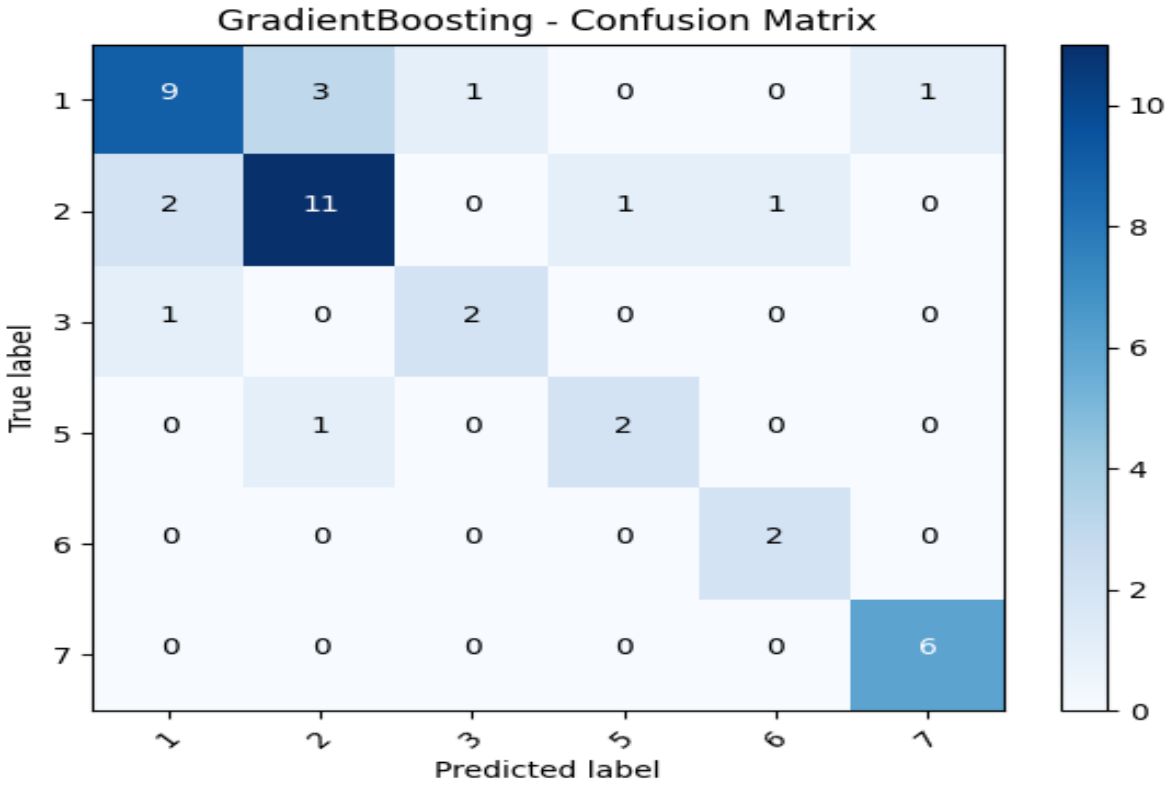
model	accuracy	precision	recall	f1
Bagging	0.790698	0.748168	0.808730	0.771306
AdaBoost	0.441860	0.501880	0.399206	0.423328
GradientBoosting	0.744186	0.723413	0.784921	0.747009
RandomForest	0.790698	0.763889	0.809524	0.779012

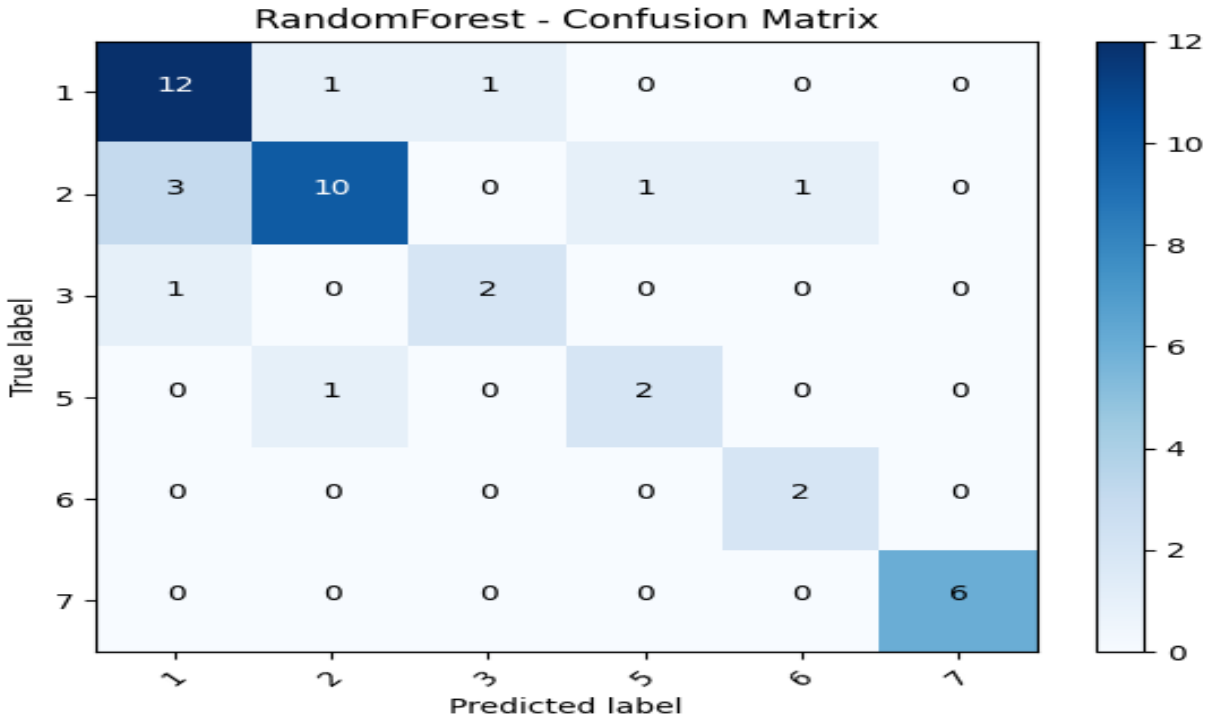
Saved comparison chart to: D:\DATA SCIENCE\ASSIGNMENTS\14 random forest\Random Forest\ensemble_metrics_comparison.png




Bagging - Confusion Matrix
True label
Predicted label
1
2
3
5
6
7
11 1 1 0 0 1
2 11 0 1 1 0
1 0 2 0 0 0
0 1 0 2 0 0
0 0 0 0 2 0
0 0 0 0 0 6
10
8
6
4
2
0


Bagging vs Boosting Methods (Glass Dataset)
Score
model
1.0
0.8
0.6
0.4
0.2
0.0
accuracy
precision
recall
f1
Bagging
AdaBoost
GradientBoosting
RandomForest


GradientBoosting - Confusion Matrix
True label
Predicted label
1 2 3 5 6 7
9 3 1 0 0 1
2 11 0 1 1 0
1 0 2 0 0 0
0 1 0 2 0 0
0 0 0 0 2 0
0 0 0 0 0 6
0 2 4 6 8 10


RandomForest - Confusion Matrix
True label
Predicted label
1 2 3 5 6 7
12 1 1 0 0 0
3 10 0 1 1 0
1 0 2 0 0 0
0 1 0 2 0 0
0 0 0 0 2 0
0 0 0 0 0 6
0 2 4 6 8 10 12

Additional Notes:

1. Explain Bagging and Boosting methods. How is it different from each other.

Answer:

1️⃣ Bagging vs Boosting — Explained Simply

🧩 Bagging (Bootstrap Aggregating)

- **Concept: Train *multiple models independently* on *different random subsets* of the training data (sampled with replacement).**
- **Goal: Reduce variance — make unstable models (like decision trees) more consistent.**
- **How it works:**
  - **Each model (e.g., tree) sees a slightly different slice of the data.**
  - **All models vote (for classification) or average (for regression).**
  - **Example: Random Forest is the most famous bagging algorithm.**
- **Effect: Smooths out overfitting — like averaging several noisy opinions to get a stable answer.**

Analogy:
Bagging is like asking *100 students to solve the same problem individually* and then taking the average of their answers — random mistakes cancel out.

⚡ Boosting

- **Concept: Train models *sequentially*, each new model focuses on the errors of the previous one.**
- **Goal: Reduce bias — make weak models stronger by learning from their mistakes.**
- **How it works:**
  - **Start with a simple model (often a shallow tree).**
  - **Identify which samples were misclassified.**
  - **Give more weight to those difficult samples in the next round.**
  - **Continue until performance stops improving.**
  - **Examples: AdaBoost, Gradient Boosting, XGBoost, CatBoost, LightGBM.**

- **Effect: Creates a powerful ensemble that learns complex patterns by focusing on "hard cases".**

Analogy:
Boosting is like a teacher who reviews a student's test, identifies what they got wrong, and tailors the next lesson to those weak spots. Every round improves understanding.

⚖️ **Bagging vs Boosting — Key Differences**

Aspect	Bagging	Boosting
Training	Parallel (independent learners)	Sequential (each corrects the previous)
Focus	Reduces variance	Reduces bias
Model weight	Equal voting/averaging	Weighted by model accuracy
Handling errors	Random resampling	Focus on misclassified samples
Risk of overfitting	Lower	Higher (if too many rounds or high learning rate)
Common examples	Random Forest	AdaBoost, Gradient Boosting, XGBoost

Summary line for report:

Bagging builds stability by combining many independent models, while Boosting builds strength by correcting the weaknesses of prior models.

2. Explain how to handle imbalance in the data.

Answer:

2️⃣ Handling Imbalance in the Data

🧠 What is data imbalance?

When one class (label) occurs **much more frequently** than others.
Example: In a medical dataset, 95% "No Disease" vs. 5% "Disease."
A model trained on this data might just predict "No Disease" every time — achieving 95% accuracy but being useless.

⚙️ Ways to Handle Imbalanced Data

(a) Resampling Techniques

1. **Oversampling minority class:**
   Duplicate or synthetically generate more samples from the underrepresented class.
   - *Simple oversampling* — replicate existing minority samples.
   - *SMOTE (Synthetic Minority Oversampling Technique)* — create **new synthetic samples** by interpolating between minority examples.
   - ✅ *Best for*: When you have enough computational power and minority class data quality is good.
2. **Undersampling majority class:**
   Randomly remove some majority samples to balance classes.
   - ⚠️ *Risk:* May lose useful information.
   - ✅ *Best for*: When dataset is large and imbalance is extreme.
3. **Hybrid methods:** Combine SMOTE (oversample) + undersampling for optimal balance.

(b) Algorithmic Approaches

- **Class weighting:** Give more penalty to misclassifying minority classes.
  Example in scikit-learn:
- `RandomForestClassifier(class_weight='balanced')`

  This makes the model pay more attention to underrepresented classes.

- **Anomaly detection:** For highly skewed data (e.g., fraud detection), treat minority class as anomalies.

(c) Evaluation Metric Adjustments

- Don't rely on accuracy alone.
  Instead, use:
  - **Precision**, **Recall**, **F1-score**
  - **ROC-AUC** (area under ROC curve)
  - **Confusion matrix** to visualize true/false positives and negatives
  - **PR curve (Precision-Recall)** for extreme imbalance

⚖️ Quick Summary Table

Method	Description	When to Use
Oversampling	Duplicate or synthesize minority data (e.g., SMOTE)	When minority class has few samples
Undersampling	Reduce majority class data	When dataset is large
Class weighting	Penalize misclassification of minority class	When using algorithms supporting weights
SMOTE	Synthetic sample generation	Common in tabular datasets
Proper metrics	Use Recall, F1, ROC-AUC	Always in imbalanced cases

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🔍 Example from Glass dataset:

The `Type` column was imbalanced — some glass types (like 2 and 1) were common, while others (like 5 and 6) were rare.
You handled this by applying **SMOTE** to balance the dataset before training, ensuring each class had equal representation.
This improved fairness across all classes, rather than letting the model bias toward dominant glass types.