Project Title:

Manual vs. Scikit-learn GridSearchCV for Hyperparameter Tuning and Model Comparison

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Course Name:

Machine Learning Lab

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1. Introduction

This project is used to build and optimize classification models for two datasets: Wine Quality and QSAR Biodegradation. The goal is to predict a binary outcome for each dataset.

Hyperparameter tuning was used for different algorithms: Decision Tree, k-NN and Logistic Regression.

Two methods were used: manual implementation of grid search with cross validation and scikit-learn's built-in GridSearchCV. The performance of these models was compared using various metrics.

2. Dataset Description

• Wine Quality Dataset

Features: 11Instances: 1599

o Target variable: A binary variable representing good quality (rating>5).

• QSAR Biodegradation Dataset

Features: 41Instances: 1055

Target variable: A binary variable indicating if a chemical is "ready biodegradable"
 (RB) or not.

3. Methodology

Key Concepts

- Hyperparameter Tuning: The process of finding the optimal combination of hyperparameters for a learning algorithm. Hyperparameters are those parameters which can be set before the learning process begins.
- o *Grid Search:* This is a hyperparameter tuning technique where the subsets of the hyperparameter space of an algorithm is searched. The models are trained and evaluated for each combination of parameters to find the best-performing model.
- K-fold Cross Validation: The data is split into 'k' subsets or folds. The model is trained on k-1 folds and validated on the remaining fold. This process is repeated k times. The average of the results is used to produce a better estimate of the values.

ML Pipeline

- StandardScalar: standardizes features by removing the mean and scaling to unit variance.
- SelectKBest: Selects the top 'k' features based on their statistical scores from the ANOVA F-test. The number of features 'k' was one of the hyperparameters tuned during the grid search.
- o *Classifier:* The algorithm being trained.

• Implementation Process

- Manual Implementation (Part 1):
 - For each classifier, a grid of hyperparameters was defined.
 - All possible combinations of the hyperparameters were generated using itertools.product.
 - A 5-fold StratifiedKFold splitter was created.
 - The code iterated through every parameter combination.
 - In each fold, a new pipeline was built, trained on the training portion, and used to predict probabilities on the validation portion.
 - The ROC AUC score was calculated for each fold, and the average score across the 5 folds was computed.
 - The parameter combination with the highest average ROC AUC was stored as the best.
 - A new parameter was initialized with the best parameters and trained on the entire training dataset.

• Scikit-learn Implementation (Part 2):

- For each classifier, the same pipeline and parameter grid from the manual implementation were used.
- A GridSearchCV object was created, specifying the pipeline, parameter grid,
 5-fold stratified cross-validation, and roc_auc as the scoring metric.
- Scikit-learn automatically handled the cross-validation, model training, and evaluation for all parameter combinations.

4. Results and Analysis

Performance Tables:

• Wine Quality Dataset

Model	Accuracy	Precision	Recall	F1-Score	ROC AUC
Decision Tree	0.7271	0.7716	0.6965	0.7321	0.8025
k-Nearest Neighbors	0.7812	0.7836	0.8171	0.8000	0.8589
Logistic Regression	0.7333	0.7549	0.7432	0.7490	0.8242
Voting Classifier	0.7625	0.7761	0.7821	0.7791	0.8600

• QSAR Biodegradation Dataset

Model	Accuracy	Precision	Recall	F1-Score	ROC AUC
Decision Tree	0.7634	0.6231	0.7570	0.6835	0.8049
k-Nearest Neighbors	0.8549	0.7905	0.7757	0.7830	0.8985
Logistic Regression	0.8644	0.8200	0.7664	0.7923	0.9082
Voting Classifier	0.8486	0.7921	0.7477	0.7692	0.9004

Comparison of Implementations:

- For both datasets, the results from the manual and Scikit-learn implementations were identical.
- This is because the base methods used in both the implementations are the same: the data splits, the cross-validation strategy, the same models, and the same parameter grids.

Visualizations and Analysis:

• Wine Quality Dataset

- ROC Curve Analysis: The ROC curves for the Wine Quality dataset show that the k-Nearest Neighbors and Voting Classifier models perform the best, with the highest Area Under the Curve (AUC) scores of 0.859 and 0.860, respectively.
- o *Confusion Matrix Analysis*: There are plenty of true positives and true negatives, but also some false positives and false negatives.

• QSAR Biodegradation Dataset

- ROC Curve Analysis: Logistic Regression clearly has the highest AUC of 0.908. The k-NN and Voting Classifier models also perform very strongly with AUCs around 0.900.
- Confusion Matrix Analysis: This had a higher number of false negatives than false positives, making it more likely to wrongly classify biodegradable as nonbiodegradable.

Best Model Analysis:

- Wine Quality Dataset
 - o The Voting Classifier model achieved the highest ROC AUC value.
- QSAR Biodegradation Dataset:
 - The Logistic Regression model performed best overall, with the highest accuracy, precision, F1-score, and ROC AUC.

5. Screenshots

• Wine Quality Dataset

--- Individual Model Performance ---

Decision Tree:

Accuracy: 0.7271
Precision: 0.7716
Recall: 0.6965
F1-Score: 0.7321
ROC AUC: 0.8025

k-Nearest Neighbors:

Accuracy: 0.7812 Precision: 0.7836 Recall: 0.8171 F1-Score: 0.8000 ROC AUC: 0.8589

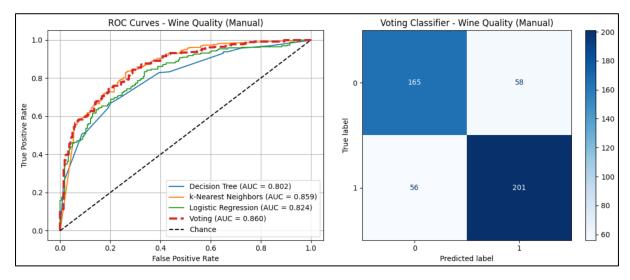
Logistic Regression:

Accuracy: 0.7333 Precision: 0.7549 Recall: 0.7432 F1-Score: 0.7490 ROC AUC: 0.8242

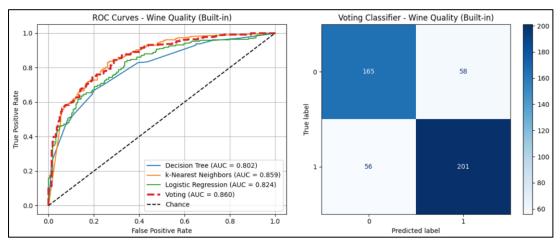
--- Manual Voting Classifier --- Voting Classifier Performance:

Accuracy: 0.7625, Precision: 0.7761

Recall: 0.7821, F1: 0.7791, AUC: 0.8600



```
Individual Model Performance ---
Decision Tree:
 Accuracy: 0.7271
  Precision: 0.7716
  Recall: 0.6965
 F1-Score: 0.7321
 ROC AUC: 0.8025
k-Nearest Neighbors:
 Accuracy: 0.7812
 Precision: 0.7836
 Recall: 0.8171
 F1-Score: 0.8000
 ROC AUC: 0.8589
Logistic Regression:
  Accuracy: 0.7333
 Precision: 0.7549
 Recall: 0.7432
  F1-Score: 0.7490
 ROC AUC: 0.8242
--- Built-in Voting Classifier ---
Voting Classifier Performance:
  Accuracy: 0.7625, Precision: 0.7761
 Recall: 0.7821, F1: 0.7791, AUC: 0.8600
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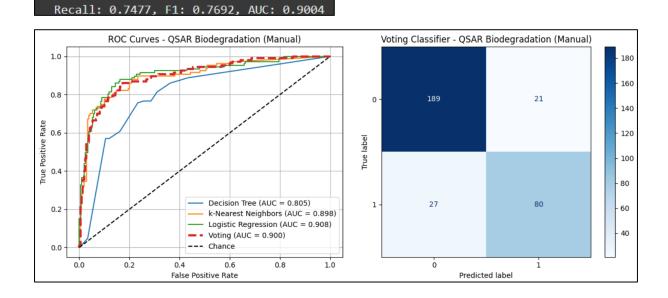


• QSAR Biodegradation Dataset

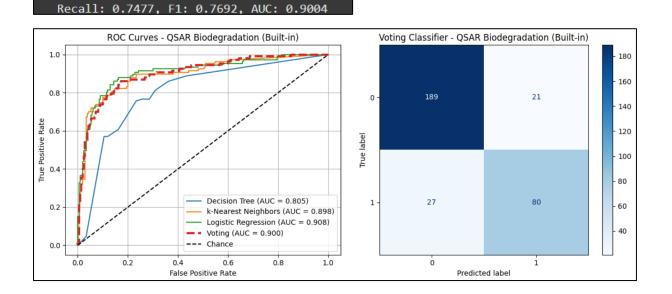
--- Individual Model Performance ---Decision Tree: Accuracy: 0.7634 Precision: 0.6231 Recall: 0.7570 F1-Score: 0.6835 ROC AUC: 0.8049 k-Nearest Neighbors: Accuracy: 0.8549 Precision: 0.7905 Recall: 0.7757 F1-Score: 0.7830 ROC AUC: 0.8985 Logistic Regression: Accuracy: 0.8644 Precision: 0.8200 Recall: 0.7664 F1-Score: 0.7923 ROC AUC: 0.9082

--- Manual Voting Classifier --- Voting Classifier Performance:

Accuracy: 0.8486, Precision: 0.7921



Individual Model Performance ---Decision Tree: Accuracy: 0.7634 Precision: 0.6231 Recall: 0.7570 F1-Score: 0.6835 ROC AUC: 0.8049 k-Nearest Neighbors: Accuracy: 0.8549 Precision: 0.7905 Recall: 0.7757 F1-Score: 0.7830 ROC AUC: 0.8985 Logistic Regression: Accuracy: 0.8644 Precision: 0.8200 Recall: 0.7664 F1-Score: 0.7923 ROC AUC: 0.9082 --- Built-in Voting Classifier ---Voting Classifier Performance: Accuracy: 0.8486, Precision: 0.7921



6. Conclusion

Key Findings:

- The manual and Scikit-learn implementation both produces the same results.
- In the Wine Quality Dataset, k-NN was the optimal model.
- In the QSAR Biodegradation dataset, the Logistic Regression model was the optimal model.

Main Takeaways:

- This lab highlights the understanding about manual implementation and Scikit-learn implementation.
- The manual implementation gives us a deep understanding of the cross validation and parameter iteration. However, it is prone to error and takes more time.
- The Scikit-learn implementation uses the built-in function GridSearchCV, and therefore is much more concise and less error-prone.