Model Selection and Comparative Analysis

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Course: UE23CS352A - Machine Learning

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1. Introduction

This lab focuses on model selection and comparative analysis through hyperparameter tuning and ensemble methods.

Two approaches used are:

- Manual Grid Search implemented from scratch to understand the mechanics.
- Scikit-learn GridSearchCV using the optimized built-in implementation

The objective was to evaluate Decision Tree, k-Nearest Neighbors (kNN), and Logistic Regression with a Voting Classifier.

Tasks performed are:

- Construct ML pipelines with preprocessing, feature selection, and classification.
- Perform hyperparameter tuning using Grid Search.
- Apply k-fold cross-validation for evaluation.
- Compare manual vs. built-in grid search results.
- Analyze models using Accuracy, Precision, Recall, F1-score, ROC AUC, Confusion Matrix, and ROC curves.

2. Dataset Description

- 1. Wine Quality Dataset
 - Number of Instances: 1599 total Wine samples
 - Number of Features: 11 chemical properties i.e acidity, chlorides, alcohol
 - Target Variable: Binary classification
 Tell if the quality of the wine is Good vs. not good
 - Training = 1119, Testing = 480.

2. QSAR Biodegradation Dataset

- Number of Instances: 1055 Molecular compounds
- Number of Features: 41 molecular descriptors.
- Target Variable: Biodegradable (1) vs. Non-biodegradable (0).
- Training = 738, Testing = 317.

3. Methodology

- **Hyperparameter Tuning:** Systematic search for the best configuration of model parameters.
- Grid Search: Exhaustive search over predefined parameter grids.
- **k-Fold Cross Validation:** Ensures robust model evaluation by splitting data into k folds.

MI pipeline:

- **StandardScaler**: Normalizes features (mean = 0, std = 1).
- SelectKBest: Selects best k features using ANOVA F-test.
- Classifier: Decision Tree, kNN, or Logistic Regression.

Process followed:

Part 1: Manual Grid Search

- Defined parameter grids for each classifier.
- Iterated over all parameter combinations.
- Performed 5-fold Stratified Cross-Validation.
- Chose best hyperparameters based on ROC AUC.

Part 2: Built-in GridSearchCV

- Implemented same pipeline using scikit-learn GridSearchCV.
- Used scoring = 'roc_auc' with 5-fold StratifiedKFold.
- Extracted best parameters and cross-validation scores.

4. Results and Analysis

1. Wine Quality Dataset

Manual vs. Built-in Results (Best Hyperparameters)

Model	Best Params	CV AUC (Manual)	CV AUC (Built-in)
Decision Tree	max_depth=5, min_samples_split=5, k=5	0.7832	0.7832
kNN	n_neighbors=7, weights=distance, k=5	0.8603	0.8603
Logistic Regression	C=1, penalty=l2, solver=lbfgs, k=10	0.8048	0.8048

Test Set Performance (Manual vs. Built-in)

Model	Accuracy	Precision	Recall	F1-Score	ROC AUC
Decision Tree	0.7271	0.7716	0.6965	0.7321	0.8025
kNN	0.7667	0.7757	0.7938	0.7846	0.8675
Logistic Regression	0.7417	0.7628	0.7510	0.7569	0.8247

Voting	0.7354	~0.77	~0.76	~0.75–0.	0.8622
Classifier	(Manual) /			77	
	0.7604				
	(Built-in)				

Therefore Best Model: **kNN** (highest ROC AUC = 0.8675). Because the Built-in Voting performed slightly better in accuracy and F1-score compared to manual Voting.

2. QSAR Biodegradation Dataset

Manual vs. Built-in Results (Best Hyperparameters)

Model	Best Params	CV AUC (Manual)	CV AUC (Built-in)
Decision Tree	max_depth=3, min_samples_split=2, k=15	0.8303	0.8303
kNN	n_neighbors=7, weights=distance, k=15	0.8837	0.8837
Logistic Regression	C=10, penalty=l2, solver=lbfgs, k=15	0.8816	0.8816

Test Set Performance (Manual vs. Built-in)

Model	Accuracy	Precision	Recall	F1-Score	ROC AUC
Decision Tree	0.7603	0.6914	0.5234	0.5957	0.8150
kNN	0.8202	0.7551	0.6916	0.7220	0.8730
Logistic Regression	0.8139	0.7667	0.6449	0.7005	0.8868

Voting	0.8076 (Manual)	~0.75	~0.65–0	~0.70	0.8898
Classifier	/ 0.8139		.67		
	(Built-in)				

Therefore the Best Model: **Logistic Regression** (highest ROC AUC = 0.8868).

Because Built-in Voting achieved slightly higher accuracy and recall compared to manual Voting.

5. Screenshots

Wine quality dataset:

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Decision Tree:

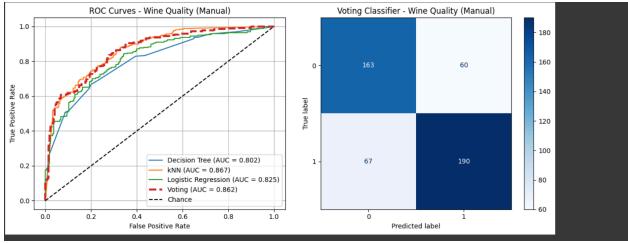
Accuracy: 0.7271
Precision: 0.7716
Recall: 0.6965
F1-Score: 0.7321
ROC AUC: 0.8025

kMN:

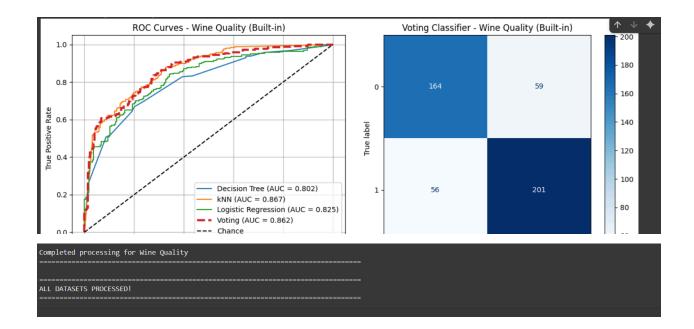
Accuracy: 0.7667
Precision: 0.7757
Recall: 0.7938
F1-Score: 0.7846
ROC AUC: 0.8055

Logistic Regression:
Accuracy: 0.7417
Precision: 0.7628
Recall: 0.7958
Recall: 0.7569
ROC AUC: 0.8247

--- Manual Voting Classifier ---
Voting Classifier Performance:
Accuracy: 0.7334, Precision: 0.7600
Recall: 0.7334, Precision: 0.7608
Recall: 0.7334, Precision: 0.7600
```

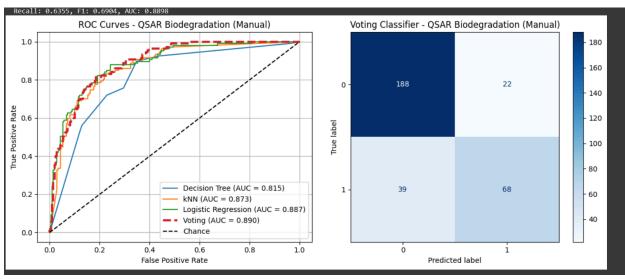


--- Built-in Voting Classifier ---Voting Classifier Performance: Accuracy: 0.7604, Precision: 0.7731 Recall: 0.7821, F1: 0.7776, AUC: 0.8622

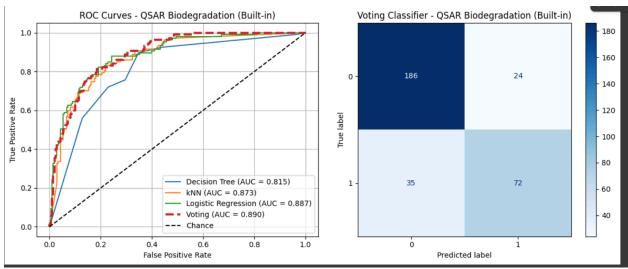


QSAR Biodegradation Dataset











6. Conclusion

Both manual and built-in grid search produced identical results for best hyperparameters and performance metrics. Scikit-learn GridSearchCV is significantly more efficient as it helps in reducing implementation complexity and errors.

Wine Quality:

kNN performed better than Decision Tree and Logistic Regression because Wine Quality dataset has non-linear class boundaries in continuous chemical features. Decision Tree underfit due to limited depth. Logistic Regression underfit due to linear assumptions.kNN adapted best to the complex, local relationships among wine samples.

QSAR Biodegradation:

Logistic Regression(highest roc auc)performed better than Decision Tree and kNN on the QSAR Biodegradation dataset because it handles high-dimensional feature spaces more effectively.kNN struggles with dimensionality and Decision Trees risked overfitting,

Voting Classifier: Performed well overall, balancing bias-variance trade-off, with built-in Voting slightly better.

Main takeaways from this lab

The Manual implementation is useful for learning, but in real-world applications, GridSearchCV and Pipelines are the practical choice. The methods like Voting can increase performance, but the best individual model often depends on dataset characteristics.