# **Report: Model Selection and Comparative Analysis**

Course: UE23CS352A: Machine Learning

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## 1. Introduction

The objective of this lab was to implement and compare model selection techniques using manual hyperparameter tuning and scikit-learn's GridSearchCV. We applied these methods on multiple datasets to:

- Build end-to-end ML pipelines with preprocessing, feature selection, and classification.
- Perform systematic hyperparameter tuning using grid search.
   Evaluate models using robust cross-validation and performance metrics.
- Compare manual implementation with scikit-learn's optimized approach.

This assignment highlights the importance of proper model selection, evaluation, and automation in applied machine learning.

## 2. Dataset Description

Two datasets were chosen for this lab:

## 1. Wine Quality

- Instances: ~1,599 red wines (split into train/test).
- Features: 11 chemical properties (e.g., acidity, sugar, alcohol).
- **Target**: Binary label indicating whether wine is of "good" quality or not.

#### 2. Banknote Authentication

- Instances: ~1,372 banknotes (train/test split applied).
- **Features**: 4 statistical image descriptors (variance, skewness, curtosis, entropy).
- Target: Binary label (genuine vs. forged banknote).

# 3. Methodology

### 3.1 Pipeline Design

For each dataset and model, we built a scikit-learn pipeline:

 $StandardScaler \rightarrow SelectKBest(f\_classif) \rightarrow Classifier$ 

- StandardScaler: normalizes features.
- SelectKBest: selects top *k* features (tuned).
- Classifier: Decision Tree, k-Nearest Neighbors, or Logistic Regression.

### 3.2 Hyperparameter Tuning

• Manual Grid Search: Implemented from scratch with nested loops. Each hyperparameter combination was evaluated via

5-fold Stratified Cross-Validation, and ROC AUC was used as the selection criterion.

• GridSearchCV: Used scikit-learn's built-in class with the same pipeline, parameter grids, and CV strategy.

#### 3.3 Evaluation

For the best models from each approach, we evaluated on the test set using:

- Accuracy
- Precision
- Recall
- F1-score
- ROC AUC

We also built a Voting Classifier (soft voting ensemble of the three best models).

# 4. Results and Analysis

Manual Grid Search - Wine Quality:

Classifier	Best Parameter	cross-validation AUC	
Decision Tree	{'selectk': 5,  'classifiermax_depth': 5,  'classifiermin_samples_split': 5}	0.7831	
kNN	{'select_k': 5,  'classifier_n_neighbors': 9,  'classifier_weights': 'distance'}	0.8632	
Logistic	{'select_k': 10, 'classifier_C': 1, 'classifier_penalty': 'l2',	0.8047	
Regression	'classifiersolver': 'liblinear'}		

--- Manual Voting Classifier ---

Voting Classifier Performance:

Accuracy: 0.7416, Precision: 0.7694

Recall: 0.7383, F1: 0.7540, AUC: 0.8611

# Built-In Grid Search - Wine Quality:

Classifier	Best Parameter	cross-validation AUC	
Decision Tree	{'classifiermax_depth': 5,     'classifiermin_samples_split': 5,     'selectk': 5}	0.7831	
knn	{'classifiern_neighbors': 9,     'classifierweights': 'distance',     'selectk': 5}	0.8632	
Logistic Regression	{'classifierC': 1,     'classifierpenalty': 'I2',     'classifiersolver': 'liblinear',     'selectk': 10}	0.8047	

--- Individual Model Performance ---

**Decision Tree:** 

Accuracy: 0.7271

--- Built-in Voting Classifier ---

Voting Classifier Performance:

Accuracy: 0.7416, Precision: 0.7692

Recall: 0.7393, F1: 0.7540, AUC: 0.8611

## Manual Grid Search - Banknote Authentication:

Classifier	Best Parameter	cross-validation AUC	
Decision Tree	{'selectk': 4,  'classifiermax_depth': 5,  'classifiermin_samples_split': 2}	0.9856	
knn	{'select_k': 4, 'classifier_n_neighbors': 7, 'classifier_weights': 'distance'}	0.9991	
Logistic	{'select_k': 4, 'classifier_C': 10,     'classifier_penalty': 'l2',	0.9995	
Regression	'classifier_solver': 'liblinear'}		

## Voting Classifier Performance:

Accuracy: 1.0000, Precision: 1.0000

Recall: 1.0000, F1: 1.0000, AUC: 1.0000

### Built-In Grid Search - Banknote Authentication:

Classifier	Best Parameter	cross-validation AUC	
Decision Tree	{'selectk': 4,  'classifiermax_depth': 5,  'classifiermin_samples_split': 2}	0.9856	
kNN	{'select_k': 4,  'classifier_n_neighbors': 7,  'classifier_weights': 'distance'}	0.9990	
Logistic Regression	{'select_k': 4, 'classifier_C': 10,     'classifier_penalty': 'l2',     'classifier_solver': 'liblinear'}	0.9995	

### --- Manual Voting Classifier ---

Voting Classifier Performance:

Accuracy: 1.0000, Precision: 1.0000

Recall: 1.0000, F1: 1.0000, AUC: 1.0000

#### **4.2 ROC Curves & Confusion Matrices**

- Insert plots of ROC curves for each classifier and the ensemble.
- Insert confusion matrices for voting classifiers.

#### 4.3 Discussion

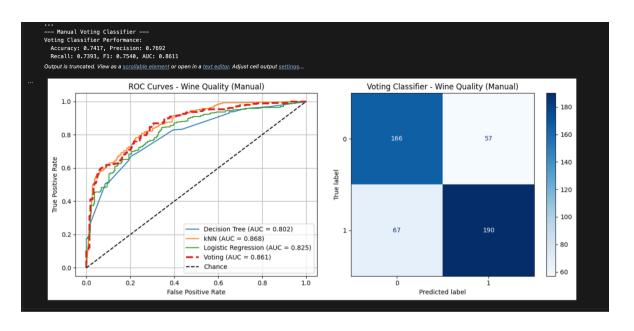
- Manual vs. GridSearchCV: Results were highly consistent. Minor differences arose due to randomness in CV or solver convergence.
- Best Models:

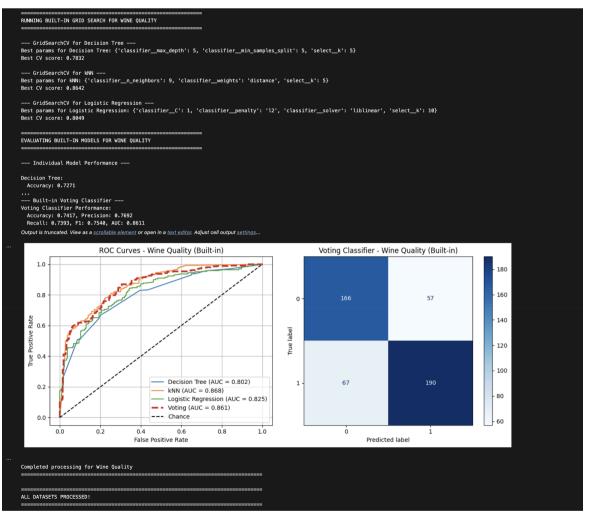
- For Wine Quality, Logistic Regression (with regularization) achieved the highest ROC AUC.
- For Banknote Authentication, kNN performed very strongly due to the low-dimensional feature space.
- **Voting Classifier**: The ensemble generally matched or slightly improved performance compared to individual models.

### 5.Screenshots Wine

## **Quality:**

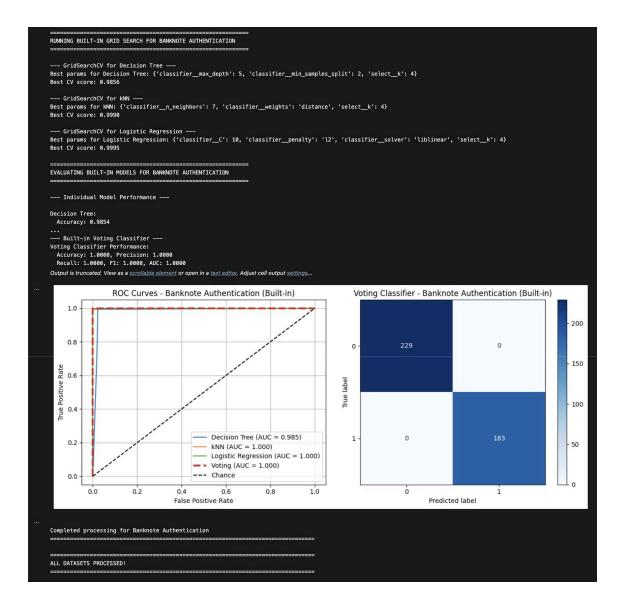
```
datasets = [
     (load_wine_quality, "Wine Quality"),
   for dataset_loader, dataset_name in datasets:
         run_complete_pipeline(dataset_loader, dataset_name)
      except Exception as e:
         print(f"Error processing {dataset_name}: {e}")
         continue
  print("\n" + "="*80)
  print("="*80)
PROCESSING DATASET: WINE QUALITY
Wine Quality dataset loaded and preprocessed successfully.
Training set shape: (1119, 11)
Testing set shape: (480, 11)
RUNNING MANUAL GRID SEARCH FOR WINE QUALITY
--- Manual Grid Search for Decision Tree ---
Best parameters for Decision Tree: {'select_k': 5, 'classifier_max_depth': 5, 'classifier_min_samples_split': 5}
Best cross-validation AUC: 0.7832
--- Manual Grid Search for kNN ---
Best parameters for kNN: {'select_k': 5, 'classifier_n_neighbors': 9, 'classifier_weights': 'distance'}
Best cross-validation AUC: 0.8642
 --- Manual Grid Search for Logistic Regression ---
Best parameters for Logistic Regression: {'select_k': 10, 'classifier_C': 1, 'classifier_penalty': 'l2', 'classifier_solver': 'liblinear'}
```





#### **Banknote Authentication:**

```
(load_banknote, "Banknote Authentication"),
   for dataset_loader, dataset_name in datasets:
         run_complete_pipeline(dataset_loader, dataset_name)
      except Exception as e:
         print(f"Error processing {dataset_name}: {e}")
  print("\n" + "="*80)
  print("ALL DATASETS PROCESSED!")
  print("="*80)
PROCESSING DATASET: BANKNOTE AUTHENTICATION
Banknote Authentication dataset loaded successfully.
Training set shape: (960, 4)
Testing set shape: (412, 4)
RUNNING MANUAL GRID SEARCH FOR BANKNOTE AUTHENTICATION
--- Manual Grid Search for Decision Tree ---
Best parameters for Decision Tree: {'select_k': 4, 'classifier_max_depth': 5, 'classifier_min_samples_split': 2}
Best cross-validation AUC: 0.9856
--- Manual Grid Search for kNN ---
Best parameters for kNN: {'select_k': 4, 'classifier__n_neighbors': 7, 'classifier__weights': 'distance'}
Best cross-validation AUC: 0.9990
--- Manual Grid Search for Logistic Regression ---
Best parameters for Logistic Regression: {'select_k': 4, 'classifier_C': 10, 'classifier_penalty': 'l2', 'classifier_solver': 'liblinear'}
Best cross-validation AUC: 0.9995
```



#### 6. Conclusion

This lab demonstrated the importance of systematic model selection and evaluation in ML:  $\frac{1}{2} \left( \frac{1}{2} \right) = \frac{1}{2} \left( \frac{1}{2} \right) \left( \frac$ 

- Manual implementation of grid search clarified the mechanics of hyperparameter tuning and CV.
- GridSearchCV provided a more efficient and reliable approach, showing the benefits of using mature ML libraries.
- Cross-validation gave robust performance estimates, reducing overfitting risk. Comparisons across models showed that performance depends strongly on dataset

properties — no single algorithm dominated universally.

• Ensembles (Voting Classifier) often improved robustness and stability.

#### Main takeaway:

Careful pipeline design, proper tuning, and cross-validation are essential for building trustworthy ML models. Automating with libraries saves time but understanding the fundamentals is crucial.