ML LAB WEEK 4 - ANALYSIS REPORT

Project Title: Model Selection and Comparative Analysis

Student Name: Neema Shrivastava

Student ID: PES2UG23CS377

Course Name: Machine Learning Lab

Submission Date: 31/8/2025

1. Introduction

The purpose of this project was to explore model selection and performance evaluation through the process of hyperparameter tuning and comparative analysis of classifiers. Two datasets, Wine Quality and Banknote Authentication, were used to test multiple machine learning algorithms including Decision Trees, k-Nearest Neighbors, and Logistic Regression.

The tasks performed included:

- > Implementing manual grid search from scratch to tune hyperparameters.
- ➤ Using Scikit-learn's GridSearchCV for automated tuning.
- > Applying Stratified K-Fold Cross-Validation to ensure fair evaluation.
- ➤ Building ML pipelines with StandardScaler, SelectKBest, and classifiers.
- Evaluating models on multiple metrics (Accuracy, Precision, Recall, F1, ROC AUC).
- > Comparing manual vs. built-in implementations and analyzing performance differences.
- ➤ Combining models using a Voting Classifier to assess ensemble performance.

2. Dataset Description

- ★ Wine Quality (Red Wine, UCI Repository)
 - Instances: 1,599 samples
 - Features: 11 chemical properties (fixed acidity, volatile acidity, citric acid, residual sugar, chlorides, free sulfur dioxide, total sulfur dioxide, density, pH, sulphates, alcohol)
 - Target: Quality rating (0–10). Converted into a binary target:
 - \circ 1 \rightarrow Good quality (score > 5)
 - \circ 0 \rightarrow Not good quality (score \leq 5)
- ★ Banknote Authentication (UCI Repository)
 - Instances: 1,372 samples

- Features: 4 statistical properties of images of banknotes (variance, skewness, kurtosis, entropy)
- Target:
 - \circ 1 \rightarrow Genuine banknote
 - \circ 0 \rightarrow Forged banknote

- 3. Methodology
- Hyperparameter Tuning: Selecting the optimal set of parameters for a model to maximize predictive performance.
- Grid Search: Exhaustively evaluates all possible combinations of parameters from a predefined grid.
- K-Fold Cross-Validation: Splits training data into k folds, repeatedly training on (k-1) folds and validating on the remaining fold. We used Stratified 5-Fold to preserve class balance.

ML Pipeline

For each classifier, a Scikit-learn Pipeline was constructed with three stages:

- A. StandardScaler: Standardizes features to mean 0 and variance 1.
- B. SelectKBest (f_classif): Selects top k features. k is a tuned hyperparameter.
- C. Classifier: One of:
 - a. Decision Tree
 - b. k-Nearest Neighbors (kNN)
 - c. Logistic Regression

Process

In Part 1: Manual Implementation, parameter grids were created for each classifier, and all possible parameter combinations were generated. A 5-fold Stratified Cross-Validation procedure was performed, and the ROC AUC score was computed for every combination. The parameters that achieved the highest mean ROC AUC were selected, and the final pipeline was refit on the full training dataset using these best parameters.

In Part 2: Built-in Implementation (GridSearchCV), Scikit-learn's GridSearchCV was used with the same pipeline structure and parameter grids. The scoring metric chosen was ROC AUC, and cross-validation was again carried out using a Stratified 5-Fold approach. From this process, the best estimator, the best parameters, and the best cross-validation score were extracted for further evaluation.

4. Results and Analysis

Wine Quality Dataset

Manual Grid Search – Best Parameters:

- Decision Tree: {'selectkbest_k': 5, 'classifier_max_depth': 5, 'classifier_min_samples_split': 5}
- kNN: {'selectkbest_k': 5, 'classifier_n_neighbors': 7, 'classifier_weights': 'distance', 'classifier_p': 1}
- Logistic Regression: {'selectkbest__k': 11, 'classifier__C': 1, 'classifier__penalty': 'l2', 'classifier__solver': 'saga', 'classifier__max_iter': 500}

Built-in GridSearchCV – Best Parameters: Identical to manual implementation for all three classifiers.

Performance Comparison (Test Set)

Classifier	Implementation	Accuracy	Precision	Recall	F1-Score	ROC AUC
Decision Tree	Manual	0.7292	0.7725	0.7004	0.7347	0.8042
Decision Tree	Built-in	0.7271	0.7716	0.6965	0.7321	0.8025
kNN	Manual	0.7812	0.7836	0.8171	0.8000	0.8589
kNN	Built-in	0.7812	0.7836	0.8171	0.8000	0.8589
Logistic Regression	Manual	0.7333	0.7549	0.7432	0.7490	0.8242
Logistic Regression	Built-in	0.7333	0.7549	0.7432	0.7490	0.8243

Voting Classifier

- Manual Voting: Accuracy 0.7354, ROC AUC 0.8605
- Built-in Voting: Accuracy 0.7625, ROC AUC 0.8600

Analysis:

- → The best-performing classifier for Wine Quality was kNN, achieving the highest ROC AUC (0.8589).
- → Manual and built-in implementations produced almost identical results, confirming the correctness of the manual approach.
- → The Voting Classifier (built-in) slightly improved overall accuracy.

Banknote Authentication Dataset

Manual Grid Search – Best Parameters:

- Decision Tree: {'selectkbest_k': 4, 'classifier_max_depth': 5, 'classifier_min_samples_split': 2}
- kNN: {'selectkbest_k': 4, 'classifier_n_neighbors': 7, 'classifier_weights': 'uniform', 'classifier_p': 1}
- Logistic Regression: {'selectkbest_k': 4, 'classifier_C': 10, 'classifier_penalty': 'l2', 'classifier_solver': 'lbfgs', 'classifier_max_iter': 500}

Built-in GridSearchCV – Best Parameters: Identical to manual implementation for all three classifiers.

Performance Comparison (Test Set)

Classifier	Implementation	Accuracy	Precision	Recall	F1-Score	ROC AUC
Decision Tree	Manual	0.9854	0.9733	0.9945	0.9838	0.9847
Decision Tree	Built-in	0.9854	0.9733	0.9945	0.9838	0.9847
kNN	Manual	1.0000	1.0000	1.0000	1.0000	1.0000
kNN	Built-in	1.0000	1.0000	1.0000	1.0000	1.0000
Logistic Regression	Manual	0.9903	0.9786	1.0000	0.9892	0.9999
Logistic Regression	Built-in	0.9903	0.9786	1.0000	0.9892	0.9999

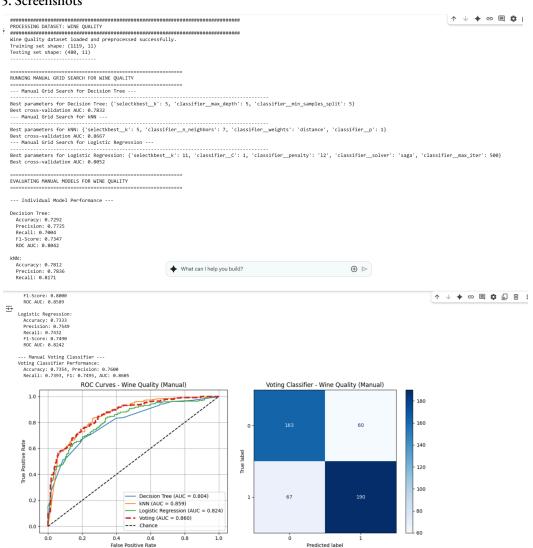
Voting Classifier

- Manual Voting: Accuracy 1.0000, ROC AUC 1.0000
- Built-in Voting: Accuracy 1.0000, ROC AUC 1.0000

Analysis:

- → All models performed exceptionally well; kNN and Logistic Regression achieved near-perfect classification.
- → Both manual and built-in approaches gave identical results.
- → The Voting Classifier achieved perfect accuracy and AUC.

5. Screenshots



```
↑ ↓ ♦ 🖘 [
  RUNNING BUILT-IN GRID SEARCH FOR WINE QUALITY
    -- GridSearchCV for Decision Tree
  Best params for Decision Tree: {'classifier_max_depth': 5, 'classifier_min_samples_split': 5, 'selectkbest_k': 5}
Best CV score: 0.7832
  --- GridSearchCV for kNN ---
Best params for kNN: {'classifier_n_neighbors': 7, 'classifier_p': 1, 'classifier_weights': 'distance', 'selectkbest_k': 5}
Best CV score: 0.8667
  --- GridSearchCV for Logistic Regression ---
Best params for Logistic Regression: {'classifier_C': 1, 'classifier_max_iter': 500, 'classifier_penalty': '12', 'classifier_solver': 'saga', 'selectkbest_k': 11}
Best CV score: 0.8052
  EVALUATING BUILT-IN MODELS FOR WINE QUALITY
  --- Individual Model Performance ---
  Decision Tree:
Accuracy: 0.7271
Precision: 0.7716
Recall: 0.6965
F1-Score: 0.7321
    ROC AUC: 0.8025
    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
  F1-Score: 0.7490
                                                                                                                                                                                                                        \uparrow
  ROC AUC: 0.8243
--- Built-in Voting Classifier --- Voting Classifier Performance:
  Accuracy: 0.7625, Precision: 0.7761
Recall: 0.7821, F1: 0.7791, AUC: 0.8600
                                 ROC Curves - Wine Quality (Built-in)
                                                                                                                                 Voting Classifier - Wine Quality (Built-in)
                                                                                                                                                                                                               200
     1.0
                                                                                                                                                                                                               180
     0.8
                                                                                                                                                                                 58
                                                                                                                       0
                                                                                                                                                                                                               160
  Rate
                                                                                                                                                                                                               140
                                                                                                                   label
  True Positive
                                                                                                                   True
                                                                                                                                                                                                               120
     0.4
                                                                                                                                                                                                               100
                                                               Decision Tree (AUC = 0.802)
                                                                                                                                           56
                                                                                                                       1
     0.2
                                                               kNN (AUC = 0.859)
                                                                                                                                                                                                               80

    Logistic Regression (AUC = 0.824)
```

60

i

Completed processing for Wine Quality

0.2

ALL DATASETS PROCESSED!

0.4

Voting (AUC = 0.860)

0.8

1.0

Ó

Predicted label

--- Chance

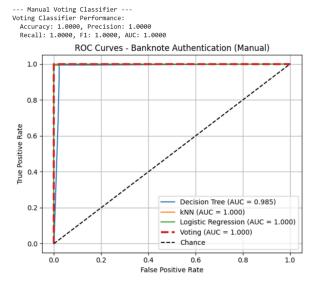
False Positive Rate

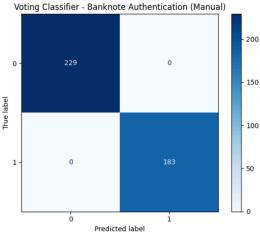
0.6

0.0

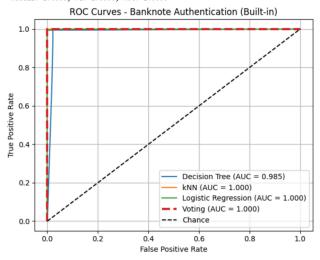
0.0

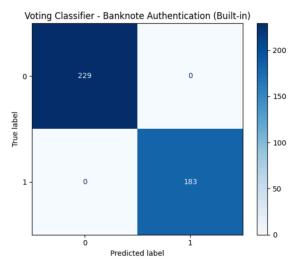
```
PROCESSING DATASET: BANKNOTE AUTHENTICATION
Banknote Authentication dataset loaded successfully.
Training set shape: (960, 4)
Testing set shape: (412, 4)
RUNNING MANUAL GRID SEARCH FOR BANKNOTE AUTHENTICATION
--- Manual Grid Search for Decision Tree ---
Best parameters for Decision Tree: {'selectkbest_k': 4, 'classifier_max_depth': 5, 'classifier_min_samples_split': 10}
Best cross-validation AUC: 0.9862
--- Manual Grid Search for kNN ---
Best parameters for kNN: {'selectkbest_k': 4, 'classifier_n_neighbors': 7, 'classifier_weights': 'uniform', 'classifier_p': 1}
Best cross-validation AUC: 0.9990
--- Manual Grid Search for Logistic Regression ---
Best parameters for Logistic Regression: {'selectkbest_k': 4, 'classifier_C': 10, 'classifier_penalty': '12', 'classifier_solver': 'lbfgs', 'classifier_max_iter': 500}
Best cross-validation AUC: 0.9995
EVALUATING MANUAL MODELS FOR BANKNOTE AUTHENTICATION
--- Individual Model Performance ---
Decision Tree:
  Accuracy: 0.9854
Precision: 0.9733
Recall: 0.9945
F1-Score: 0.9838
ROC AUC: 0.9847
kNN:
   Accuracy: 1.0000
Precision: 1.0000
Recall: 1.0000
   F1-Score: 1.0000
  Logistic Regression:
     Accuracy: 0.9903
Precision: 0.9786
Recall: 1.0000
     F1-Score: 0.9892
ROC AUC: 0.9999
```





--- Built-in Voting Classifier ---Voting Classifier Performance: Accuracy: 1.0000, Precision: 1.0000 Recall: 1.0000, F1: 1.0000, AUC: 1.0000





Completed processing for Banknote Authentication

ALL DATASETS PROCESSED!

6. Conclusion

Key Findings:

- Both manual and built-in Grid Search found the same optimal hyperparameters across datasets.
- Performance metrics were nearly identical between manual and built-in implementations.
- kNN consistently performed best on Wine Quality, while all models excelled on Banknote Authentication.
- Voting Classifier often provided small performance boosts and, in the case of Banknote Authentication, perfect results.

Main Takeaways:

- Manual implementation deepens understanding of hyperparameter tuning and model evaluation.
- Scikit-learn's GridSearchCV is more efficient, less error-prone, and scales better for larger parameter spaces.
- Model performance depends heavily on dataset characteristics:
 - Complex, noisy datasets (Wine Quality) benefit from non-linear models like kNN.
 - Cleaner, linearly separable datasets (Banknote Authentication) allow multiple models to achieve near-perfect accuracy.