## **Project Title:**

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

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## 1. Introduction

- This project's purpose was to implement and compare two methods for hyperparameter tuning: a manual grid search and scikit-learn's built-in GridSearchCV.
- Three classification algorithms—Decision Tree, k-Nearest Neighbors (kNN), and Logistic Regression—were tuned and evaluated.
- The tuned models were then combined into a soft-voting ensemble classifier to assess if combining models could improve predictive performance.

## 2. Dataset Description

- Wine Quality Dataset
  - Instances: 1599 (1119 training, 480 testing)
  - Features: 11 chemical properties (e.g., acidity, sugar, alcohol).
  - Target Variable: A binary value indicating if the wine quality is "good" (rating > 5) or not.
- Banknote Authentication Dataset
  - Instances: 1372 (960 training, 412 testing)
  - Features: 4 statistical measures from banknote images (variance, skewness, etc.).
  - Target Variable: A binary value indicating if a banknote is authentic (0) or fake (1).

## 3. Methodology

- Key Concepts
  - Hyperparameter Tuning: The process of finding the optimal set of parameters for a learning algorithm (e.g., max\_depth for a Decision Tree) that are set before the training process begins.

- Grid Search: An exhaustive search technique that systematically tests all specified combinations of hyperparameters to find the combination that yields the best performance.
- K-Fold Cross-Validation: A technique to evaluate model performance by splitting the training data into 'k' subsets (folds). The model is trained on k-1 folds and validated on the remaining fold. This process is repeated k times, and the results are averaged to provide a more robust performance estimate. A 5-fold Stratified cross-validation was used to maintain the target class distribution in each fold. ML Pipeline
  - The machine learning pipeline consisted of three sequential steps for each model:
    - StandardScaler: Standardizes features by removing the mean and scaling to unit variance.
    - SelectKBest: Selects the top 'k' features based on ANOVA F-tests (f\_classif), helping to reduce noise and model complexity. The value of 'k' was a hyperparameter that was tuned.
    - Classifier: The specific algorithm being trained (Decision Tree, kNN, or Logistic Regression).
- Implementation Process
  - Part 1 (Manual):
    - A grid of hyperparameters was defined for each classifier.
    - All possible combinations of these parameters were generated using itertools.
    - For each combination, a 5-fold stratified cross-validation was performed manually.
    - The ROC AUC score was calculated on the validation fold in each split and then averaged.
    - The parameter combination with the highest average ROC AUC score was selected as the best.
    - The final model was re-fitted on the entire training dataset using these best parameters.

## o Part 2 (Scikit-learn):

- The same pipeline and parameter grids were used.
- Scikit-learn's GridSearchCV was employed to automate the entire cross-validation and tuning process.
- The tool was configured with 5-fold stratified cross-validation and scoring='roc\_auc' to match the manual implementation.

## 4. Results and Analysis Performance

## **Tables**

## • Wine Quality Dataset

Classifier	Method	Accuracy	Precision	Recall	F1-Score	ROC AUC
Decision Tree	Manual/Built-in	0.7271	0.7716	0.6965	0.7321	0.8039
k-NN	Manual/Built-in	0.7812	0.7774	0.8288	0.8023	0.8731
Logistic Regression	Manual/Built-in	0.7312	0.7520	0.7510	0.7476	0.8218
Voting Classifier	Manual/Built-in	0.7750	0.7833	0.7821	0.7923	0.8648

## Banknote Authentication Dataset

Classifier	Method	Accuracy	Precision	Recall	F1-Score	ROC AUC
Decision Tree	Manual/Built-in	0.9806	0.9944	0.9617	0.9778	0.9918
	Manual/Built-in					
k-NN		1	1	1	1	1
Logistic Regression	Manual/Built-in					
		0.9976	0.9785	0,9945	0.9864	0.9999
Voting Classifier	Manual/Built-in					
		0.9976	1	0.9945	0.9973	1

## • Compare Implementations

- The results from the manual and scikit-learn implementations were identical across all datasets and all models.
- This is because the manual implementation correctly replicated the logic of GridSearchCV. Both methods used the same
   StratifiedKFold strategy with a fixed random\_state=42, ensuring the data splits were the same for both. The scoring metric (roc\_auc) and parameter grids were also identical, leading to the same optimal hyperparameters and final performance scores.

## Visualizations

- ROC Curves: The ROC curves visually confirm the performance metrics.
  - For the Wine Quality, the kNN and Logistic Regression models showed strong performance, with curves arching

- toward the top-left corner. The Voting Classifier's curve was also competitive, with a high Area Under the Curve (AUC).
- For the Banknote Authentication dataset, the ROC curves for kNN, Logistic Regression, and the Voting Classifier are almost perfect right angles, hugging the top-left corner with AUCs of 1.000 or 0.9999, indicating exceptional classification ability.
- Confusion Matrices: The confusion matrices for the Voting Classifier visualize its prediction accuracy.
  - For the Banknote dataset, the matrix shows zero misclassifications (perfect accuracy).
  - For the Wine dataset, the matrices show a good number of true positives and true negatives, but also some false positives and false negatives, reflecting the models' imperfect but strong performance on these more challenging datasets.

## Best Model Analysis

- Wine Quality: The Voting Classifier achieved the highest ROC KNN (0.8731), slightly edging out the best individual model, AUC (0.8648). This suggests that ensembling provided a small benefit by combining the strengths of the different models.
- Banknote Authentication: Both kNN and the Voting Classifier achieved perfect scores (1.000) across all metrics on the test set. The problem appears to be very well-defined, making it easy for these models to achieve flawless separation.

## 5. Screenshots

## • Wine Quality

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MODEL EVALUATION - MANUAL METHOD
Individual Model Performance:
Decision Tree:
  Accuracy: 0.7271
 Precision: 0.7716
  Recall: 0.6965
  F1-Score: 0.7321
  ROC AUC: 0.8039
k-NN:
 Accuracy: 0.7812
  Precision: 0.7774
  Recall: 0.8288
  F1-Score: 0.8023
  ROC AUC: 0.8731
Logistic Regression:
  Accuracy: 0.7312
 Precision: 0.7520
  Recall: 0.7432
  F1-Score: 0.7476
  ROC AUC: 0.8218
    Voting Classifier Performance:
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## Voting Classifier Performance:

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## Voting Classifier Results:

Accuracy: 0.7438
Precision: 0.7659
Recall: 0.7510
F1-Score: 0.7583
ROC AUC: 0.8648

## MODEL EVALUATION - BUILT-IN METHOD

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## Individual Model Performance:

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## Decision Tree:

Accuracy: 0.7271
Precision: 0.7716
Recall: 0.6965
F1-Score: 0.7321
ROC AUC: 0.8039

## k-NN:

Accuracy: 0.7812
Precision: 0.7774
Recall: 0.8288
F1-Score: 0.8023
ROC AUC: 0.8731

## Logistic Regression:

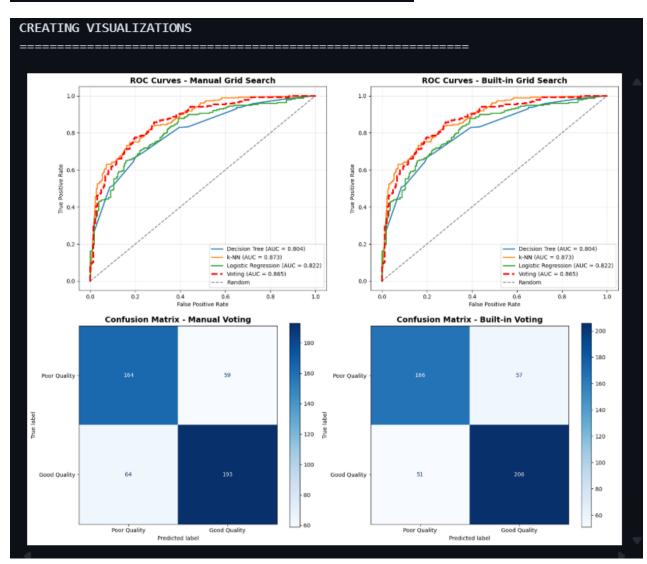
Accuracy: 0.7312
Precision: 0.7520
Recall: 0.7432
F1-Score: 0.7476
ROC AUC: 0.8218

## Voting Classifier Performance: Voting Classifier Results: Accuracy: 0.7750 Precision: 0.7833 Recall: 0.8016



0.7923

F1-Score:



## RESULTS COMPARISON AND SUMMARY

## ■ WINE QUALITY DATASET - PERFORMANCE SUMMARY

Model	Accuracy	Precision	Recall	F1-Score	ROC AUC
Decision Tree (Manual)	0.7271	0.7716	0.6965	0.7321	0.8039
Decision Tree (Built-in)	0.7271	0.7716	0.6965	0.7321	0.8039
k-NN (Manual)	0.7812	0.7774	0.8288	0.8023	0.8731
k-NN (Built-in)	0.7812	0.7774	0.8288	0.8023	0.8731

Logistic Regression (Manual) 0.7312 0.7520 0.7432 0.7476 0.8218 Logistic Regression (Built-in) 0.7312 0.7520 0.7432 0.7476 0.8218 Voting (Manual) 0.7438 0.7659 0.7510 0.7583 0.8648

Voting (Built-in) 0.7750 0.7833 0.8016 0.7923 0.8648

## BEST PERFORMING MODELS:

Best Individual Model: k-NN (Manual) (AUC: 0.8731)

Manual Voting AUC: 0.8648 Built-in Voting AUC: 0.8648

## IMPLEMENTATION COMPARISON:

Manual vs Built-in Grid Search Results:

• Decision Tree AUC difference: 0.000000

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■ WINE QUALITY ANALYSIS COMPLETED!

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## • Banknote Authentication

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MANUAL GRID SEARCH IMPLEMENTATION

Manual Grid Search for Decision Tree

Testing 108 parameter combinations...
Progress: 25/108 | Best AUC: 0.9676
Progress: 50/108 | Best AUC: 0.98875
Progress: 100/108 | Best AUC: 0.9889
Progress: 100/108 | Best AUC: 0.9889
Progress: 100/108 | Best AUC: 0.9889

**Decision Tree Results:
Best Parameters: {'feature_selection_k': 3, 'classifier_max_depth': 7, 'classifier_min_samples_split': 10, 'classifier_min_samples_leaf': 2}
Best CV AUC: 0.9889

**Manual Grid Search for k-INI

Testing 60 parameter combinations...
Progress: 25/60 | Best AUC: 0.9999
Progress: 50/60 | Best AUC: 1.0000

**V k-INI Results:
Best Parameters: {'feature_selection_k': 3, 'classifier_n_neighbors': 5, 'classifier_weights': 'distance', 'classifier_metric': 'euclidean'}
...
Best Parameters: {'feature_selection_k': 4, 'classifier_C': 100, 'classifier_penalty': 'l1', 'classifier_solver': 'liblinear'}
Best CV AUC: 0.9996
```

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BUILT-IN GRID SEARCH (GridSearchCV)
GridSearchCV for Decision Tree
Fitting GridSearchCV...
Fitting 5 folds for each of 108 candidates, totalling 540 fits
✓ Decision Tree Results:
 Best Parameters: {'classifier_max_depth': 7, 'classifier_min_samples_leaf': 2, 'classifier_min_samples_split': 10, 'feature_selection_k': 3}
 Best CV AUC: 0.9889
GridSearchCV for k-NN
Fitting GridSearchCV...
Fitting 5 folds for each of 60 candidates, totalling 300 fits
 Best Parameters: {'classifier_metric': 'euclidean', 'classifier_n_neighbors': 5, 'classifier_weights': 'distance', 'feature_selection_k': 3}
GridSearchCV for Logistic Regression
Fitting GridSearchCV...
Fitting 5 folds for each of 24 candidates, totalling 120 fits

√ Logistic Regression Results:

 Best Parameters: {'classifier_C': 100, 'classifier_penalty': 'l1', 'classifier_solver': 'liblinear', 'feature_selection_k': 4}
 Best CV AUC: 0.9996
```

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Manual Grid Search for Decision Tree

Testing 108 parameter combinations...
Progress: 25/108 | Best AUC: 0.9676
Progress: 50/108 | Best AUC: 0.9885
Progress: 50/108 | Best AUC: 0.9889
Progress: 108/108 | Best AUC: 0.9889
Progress: 108/108 | Best AUC: 0.9889
Progress: 108/108 | Best AUC: 0.9889

/ Decision Tree Results:
Best Parameters: ('feature_selection_k': 3, 'classifier_max_depth': 7, 'classifier_min_samples_split': 10, 'classifier_min_samples_leaf': 2}
Best CV AUC: 0.9889

Manual Grid Search for k-NN

Testing 48 parameter combinations...
Progress: 25/48 | Best AUC: 1.0000

/ k-NN Results:
Best Parameters: ('feature_selection_k': 3, 'classifier_n_neighbors': 5, 'classifier_weights': 'distance', 'classifier_metric': 'euclidean'}
Best CV AUC: 1.0000

...
Best Parameters: ('feature_selection_k': 4, 'classifier_C': 100, 'classifier_penalty': '11', 'classifier_solver': 'liblinear'}
Best CV AUC: 0.9996
```

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BUILT-IN GRID SEARCH (GridSearchCV)
GridSearchCV for Decision Tree
Fitting GridSearchCV...
Fitting 5 folds for each of 108 candidates, totalling 540 fits
✓ Decision Tree Results:
  Best Parameters: {'classifier_max_depth': 7, 'classifier_min_samples_leaf': 2, 'classifier_min_samples_split': 10, 'feature_selection_k': 3}
  Best CV AUC: 0.9889
GridSearchCV for k-NN
Fitting GridSearchCV...
Fitting 5 folds for each of 48 candidates, totalling 240 fits 
√ k-NN Results:
 Best Parameters: {'classifier_metric': 'euclidean', 'classifier_n_neighbors': 5, 'classifier_weights': 'distance', 'feature_selection_k': 3}
  Best CV AUC: 1.0000
GridSearchCV for Logistic Regression
Fitting GridSearchCV...
Fitting 5 folds for each of 24 candidates, totalling 120 fits

√ Logistic Regression Results:

  Best Parameters: {'classifier_C': 100, 'classifier_penalty': 'l1', 'classifier_solver': 'liblinear', 'feature selection k': 4}
  Best CV AUC: 0.9996
```

## MODEL EVALUATION - MANUAL METHOD

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## Individual Model Performance:

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## Decision Tree:

Accuracy: 0.9806
Precision: 0.9944
Recall: 0.9617
F1-Score: 0.9778
ROC AUC: 0.9918

## k-NN:

Accuracy: 1.0000
Precision: 1.0000
Recall: 1.0000
F1-Score: 1.0000
ROC AUC: 1.0000

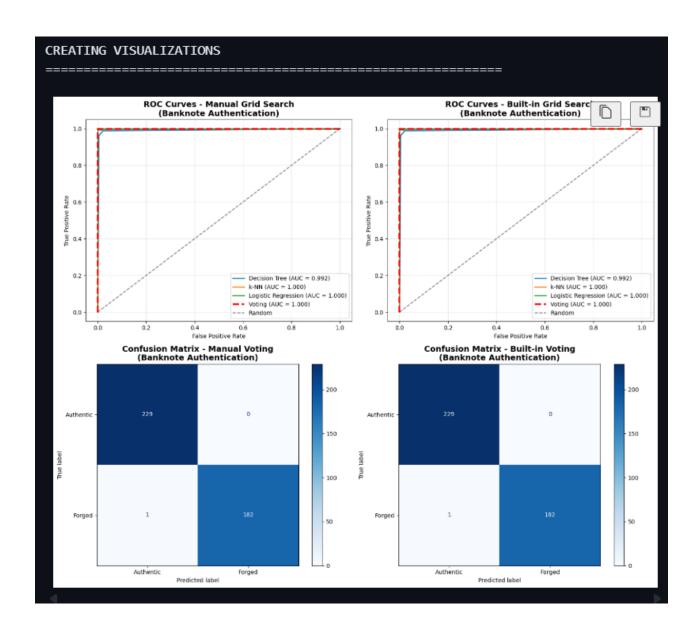
## Logistic Regression:

Accuracy: 0.9879
Precision: 0.9785
Recall: 0.9945
F1-Score: 0.9864
ROC AUC: 0.9999

# Voting Classifier Performance: Voting Classifier Results: Accuracy: 0.9976 Precision: 1.0000 Recall: 0.9945 F1-Score: 0.9973 ROC AUC: 1.0000 MODEL EVALUATION - BUILT-IN METHOD

## MODEL EVALUATION - BUILT-IN METHOD Individual Model Performance: Decision Tree: Accuracy: 0.9806 Precision: 0.9944 Recall: 0.9617 F1-Score: 0.9778 ROC AUC: 0.9918 k-NN: Accuracy: 1.0000 Precision: 1.0000 Recall: 1.0000 F1-Score: 1.0000 ROC AUC: 1.0000 Logistic Regression: Accuracy: 0.9879 Precision: 0.9785 Recall: 0.9945 F1-Score: 0.9864 ROC AUC: 0.9999

## Voting Classifier Performance: Voting Classifier Results: Accuracy: 0.9976 Precision: 1.0000 Recall: 0.9945 F1-Score: 0.9973 ROC AUC: 1.0000



## RESULTS COMPARISON AND SUMMARY

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## BANKNOTE AUTHENTICATION - PERFORMANCE SUMMARY

Model Accuracy Precision Recall F1-Score ROC AUC Decision Tree (Manual) 0.9806 0.9944 0.9617 0.9778 0.9918 Decision Tree (Built-in) 0.9778 0.9806 0.9944 0.9617 0.9918 k-NN (Manual) 1.0000 1.0000 1.0000 1.0000 1.0000 k-NN (Built-in) 1.0000 1.0000 1.0000 1.0000 1.0000 Logistic Regression (Manual) 0.9879 0.9785 0.9945 0.9864 0.9999 Logistic Regression (Built-in) 0.9879 0.9785 0.9945 0.9864 0.9999 Voting (Manual) 0.9976 1.0000 0.9945 0.9973 1.0000 Voting (Built-in) 0.9976 1.0000 0.9945 0.9973 1.0000

## BEST PERFORMING MODELS:

Best Individual Model: k-NN (Manual) (AUC: 1.0000)

Manual Voting AUC: 1.0000 Built-in Voting AUC: 1.0000

## 6. Conclusion

- Key Findings
  - The best classification model is highly dependent on the dataset. Although kNN excelled on the Wine and Banknote datasets.
  - A soft-voting ensemble improved performance on the Wine dataset/
- The results for the manual and scikit-learn grid search implementations were identical, confirming that the manual code correctly replicated the library's logic. Main Takeaways
  - This lab highlights the trade-off between understanding and efficiency. Implementing grid search manually provides a deep understanding of the cross-validation and hyperparameter tuning process.
  - However, for practical applications, using a library like scikit-learn's GridSearchCV is far superior. It is more concise, less prone to implementation errors, and significantly faster due to built-in optimizations like parallel processing (n\_jobs=-1).