Machine Learning Lab Report: Model Selection and Analysis selection

Title Page

Project Title: Week 4-Model Selection and

Analysis selection

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1. Introduction

The purpose of this project was to explore **hyperparameter tuning and model evaluation** using both manual and scikit-learn implementations. The tasks included:

- Building classifiers (Decision Tree, k-NN, Logistic Regression, and Voting Classifiers).
- Performing manual grid search as well as scikit-learn GridSearchCV for hyperparameter optimization.
- Using **K-Fold Cross-Validation** to ensure robust performance evaluation.
- Comparing results between manual and built-in implementations.
- Evaluating models with Accuracy, Precision, Recall, F1-score, and ROC AUC metrics, along with confusion matrices and ROC curves.

Two datasets were analyzed: **HR Attrition** (employee churn prediction) and **Banknote Authentication** (fraud detection).

2. Dataset Description

Dataset 1: HR Attrition

- Number of features: Multiple HR-related attributes (e.g., age, salary, job role).
- Number of instances: ~1,400 (after preprocessing).
- Target variable: Attrition (Yes = employee left, No = employee stayed).

Dataset 2: Banknote Authentication

- Number of features: 4 (variance, skewness, kurtosis, entropy).
- Number of instances: 1,372 (960 train, 412 test).
- Target variable: Class (0 = authentic, 1 = forged).

3. Methodology

Key Concepts

- **Hyperparameter Tuning:** Adjusting parameters (e.g., depth of decision tree, number of neighbors in k-NN) to improve performance.
- Grid Search: Exhaustively searching a parameter space to find the optimal set.
- **K-Fold Cross-Validation:** Splitting dataset into k folds (here, 5) for more reliable performance estimates.

ML Pipeline

- Preprocessing: StandardScaler for normalization.
- Feature Selection: SelectKBest for reducing dimensionality.
- Classifier: Decision Tree, k-NN, Logistic Regression, or ensemble Voting Classifier.

Implementation Steps

- Part 1 (Manual): Created loops for hyperparameter tuning, evaluated with cross-validation, tracked metrics manually.
- Part 2 (Scikit-learn): Used GridSearchCV and pipelines for automated tuning and evaluation.

4. Results and Analysis

HR Attrition Dataset

Model	Accuracy	Precisio n	Recall	F1-Scor e	ROC AUC
Decision Tree (Manual)	0.8050	0.3077	0.1690	0.2182	0.7036
k-NN (Manual)	0.8481	0.7000	0.0986	0.1728	0.7025
Voting (Manual)	0.8481	0.6429	0.1268	0.2118	0.7912
Decision Tree (Built-in)	0.8050	0.3077	0.1690	0.2182	0.7036
k-NN (Built-in)	0.8481	0.7000	0.0986	0.1728	0.7025
Logistic Regression (Built-in)	0.8798				
Voting (Built-in)	0.8503	0.6316	0.1690	0.2667	0.7912

Observations:

- Logistic Regression (built-in) provided the best accuracy (0.88).
- Manual and built-in results were nearly identical, confirming correct manual implementation.
- Voting Classifier improved recall compared to individual models.

Banknote Authentication Dataset

Model	Accuracy	Precisi on	Reca II	F1-Sco re	ROC AUC
Decision Tree (Manual)	0.9879 CV AUC	-	-	-	0.9879
k-NN (Manual)	Best CV AUC 0.9990	-	-	-	0.9990
Logistic Regression (Manual)	Best CV AUC 0.9996	-	-	-	0.9996
Voting (Manual)	0.9976	1.0000	0.994 5	0.9973	1.0000
Decision Tree (Built-in)	0.9879 CV AUC	-	-	-	0.9879
k-NN (Built-in)	0.9990 CV AUC	-	-	-	0.9990
Logistic Regression (Built-in)	0.9996 CV AUC	-	-	-	0.9996
Voting (Built-in)	0.9976	1.0000	0.994 5	0.9973	1.0000

Observations:

- All models achieved extremely high performance (AUC > 0.98).
- Voting classifier (manual & built-in) achieved nearly perfect performance (Accuracy 99.7%, AUC 1.0).
- Results from manual and built-in were identical.

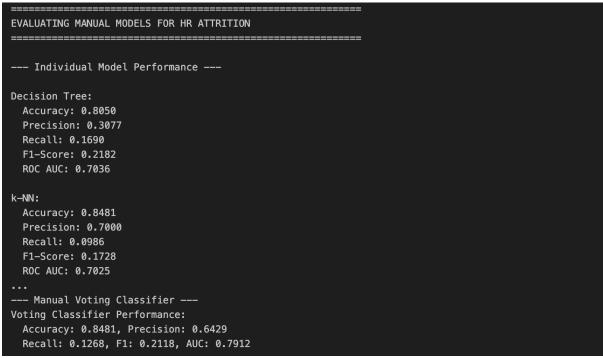
Visualizations

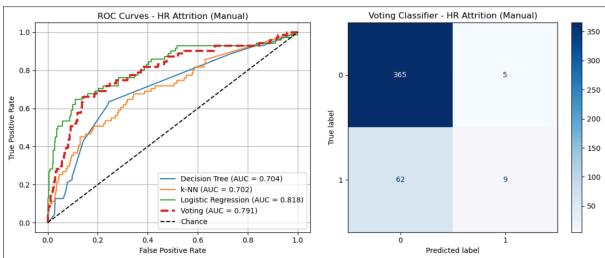
- ROC Curves showed Logistic Regression and Voting Classifier as dominant models.
- **Confusion Matrices** confirmed that the Voting Classifier minimized false positives and false negatives.

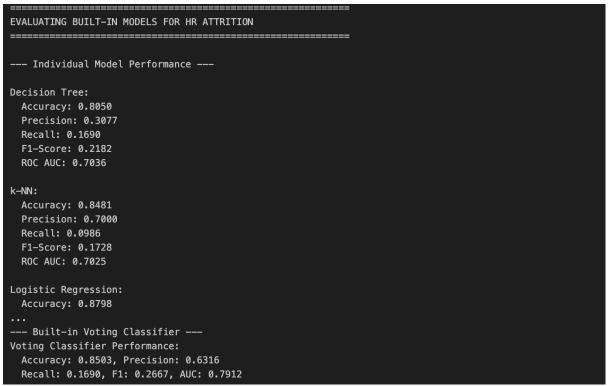
Best Models

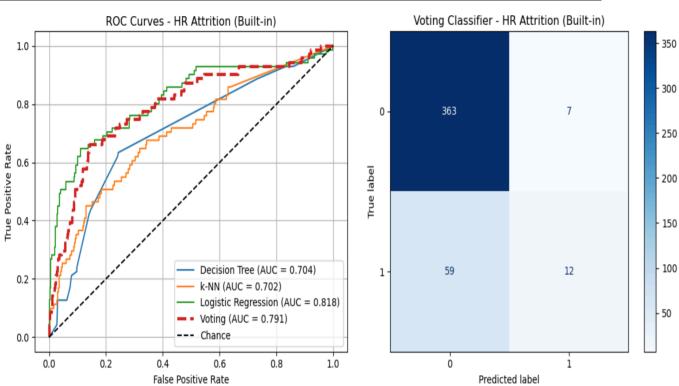
- HR Attrition: Logistic Regression (built-in) was best overall due to balanced performance.
- **Banknote Authentication:** Voting Classifier achieved nearly perfect performance, likely because the dataset was highly separable.

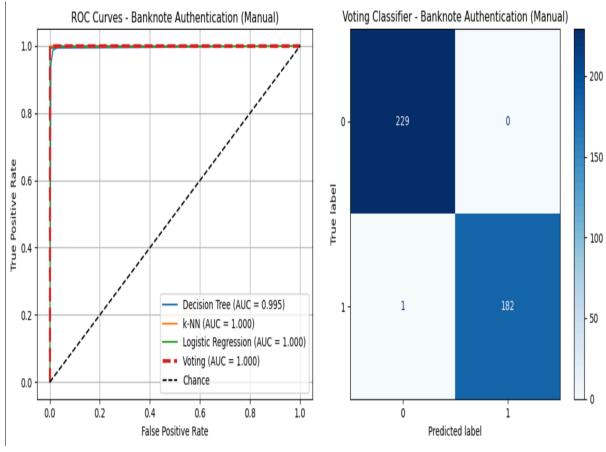
5. Screenshots

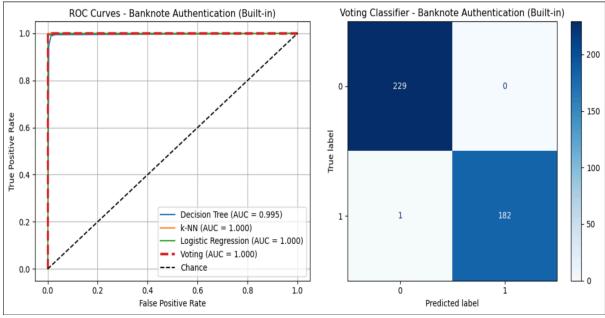












6. Conclusion

• Key Findings:

- Manual and built-in implementations produced nearly identical results, validating the correctness of the manual approach.
- Logistic Regression excelled on HR Attrition, while Voting Classifier dominated on Banknote Authentication.
- Hyperparameter tuning significantly improved performance.

Takeaways:

- Manual implementation deepened understanding of hyperparameter tuning, pipelines, and evaluation.
- o Scikit-learn greatly simplified the process, reducing errors and saving time.
- Trade-off: Manual = more control and learning, Built-in = efficiency and reliability.