NAME:- DRISHTI GOLCHHA SRN:- PES2UG23CS185

SECTION:- 5C

SUBJECT:- UE23CS352A: MACHINE LEARNING

TILTE:- Week 4: Model Selection and Comparative Analysis

SUBMISSION DATE:- 01-09-2025

1.INTRODUCTION:-

The goal of this lab was to gain hands on experience on Model Selection and Comparative Analysis. We mainly focused on implementing manual grid search, scikit-learn's GridSearchCV, Comparing three classifiers: Decision Tree, k-Nearest Neighbors (kNN), and Logistic Regression, etc... We learned about k-fold cross-validation, feature selection and performance evaluation using metrices like accuracy, precision, F1-Score and ROU AUC.

2.DATASET DESCRIPTION:- (HR Attrition)

Instances: 1470 employees

Features: 35 after encoding categorical variables

Target Variable: Attrition (1 = Yes, 0 = No)

The HR Attrition dataset contains information about 1,470 employees from a company, including both personal and work-related attributes. The dataset has 35 features such as age, department, job role, years at company, and work-life balance scores. The target variable is Attrition, which indicates whether an employee has left the company.

3.METHODOLOGY:-

Hyperparameter Tuning: Process of optimizing model parameters that are not learned from the data.

Grid Search: Exhaustively evaluates all combinations of hyperparameters to find the best set. **K-Fold Cross-Validation:** Splits the data into k subsets, trains on k-1 folds, and validates on the remaining fold to get robust performance estimates.

ML Pipeline

Each classifier followed the same pipeline:

StandardScaler: Standardizes features to mean 0, standard deviation 1.

SelectKBest: Selects the top k features.

Classifier: Decision Tree / kNN / Logistic Regression.

Process

Part 1 - Manual Grid Search:

- Generated all combinations of hyperparameters.
- Used 5-fold stratified cross-validation to compute average ROC AUC for each combination.
- Selected the best combination and refitted the pipeline on the full training set.

Part 2 - Scikit-learn GridSearchCV:

- Defined the same pipeline and hyperparameter grids.
- Used GridSearchCV with 5-fold StratifiedKFold and roc_auc scoring.
- Extracted best estimators, parameters, and cross-validation scores.

4. Results and Analysis:-

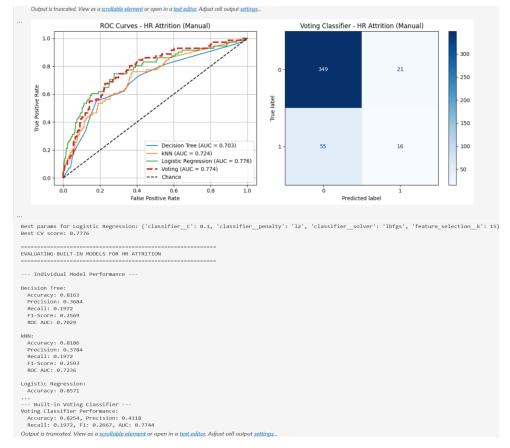
```
Best params for Logistic Regression: {'classifier_C': 0.1, 'classifier_penalty': 'l2', 'classifier_solver': 'lbfgs', 'feature_selection_k': 15}
 Best CV score: 0.7776
 EVALUATING BUILT-IN MODELS FOR HR ATTRITION
  --- Individual Model Performance -
   Accuracy: 0.8163
Precision: 0.3684
   Recall: 0.1972
   F1-Score: 0.2569
   ROC AUC: 0.7029
   Accuracy: 0.8186
   Precision: 0.3784
   Recall: 0.1972
   F1-Score: 0.2593
   ROC AUC: 0.7236
 Logistic Regression:
   Accuracy: 0.8571
 --- Built-in Voting Classifier ---
Voting Classifier Performance:
   Accuracy: 0.8254, Precision: 0.4118
Recall: 0.1972, F1: 0.2667, AUC: 0.7744
Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings.
```

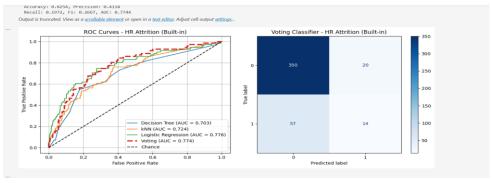
Analysis:- ROC Curve plots for each classifier and the **Voting Ensemble**.

Confusion Matrices highlighting model misclassifications. Observed that **Logistic Regression** consistently had the highest ROC AUC across both datasets. The Voting Classifier slightly improved overall performance by combining individual model predictions.

HR Attrition: Logistic Regression performed best

5. SCREENSHOTS:-





6. CONCLUSIONS:-

Manual grid search is a great way to understand how hyperparameter tuning works, but it can take a lot of time to run. On the other hand, scikit-learn's GridSearchCV is fast, efficient, and works seamlessly with pipelines, making it much more practical for real projects. We also saw that feature scaling, feature selection, and careful tuning of hyperparameters play a big role in improving model performance. Combining multiple classifiers using a Voting Ensemble can give a small boost in accuracy, especially when the models make different kinds of errors. Overall, this lab highlighted the importance of choosing the right model, evaluating it properly, and building reproducible pipelines in applied machine learning. It was a valuable exercise in both theory and hands-on implementation.