P2 - Diabetes prediction models

An overview of classifier algorithms

Alex Beauchamp - Otman Ezzayat Maid - Joan Gómez Català - Matija Jakovac - Álvaro Monclús Muñoz

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Format of presentation

1. Description of the original data
2. Preprocessing
3. Evaluation criteria of data mining models
4. Execution of different machine learning methods
   a. Naive Bayes
   b. K-NN
   c. Decision Trees
   d. Support Vector Machines
   e. Meta-Learning Algorithms
5. Comparison and conclusions

1. Description of the original data

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Presentation of dataset

- Origin: Kaggle.com
- Balanced diabetes results
  - Sourced from a survey named “Behavioral Risk Factor Surveillance System”
- 70,692 records
- Key variables:
  - Diabetes or Pre-diabetic vs Non-diabetic
  - High Blood Pressure
  - High BMI
  - Heart Conditions
  - Age
  - etc.

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Description of metadata P1

Kaggle URL : https://www.kaggle.com/code/alexteboul/diabetes-health-indicators-dataset-notebook

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Description of metadata P2

Kaggle URL : https://www.kaggle.com/code/alexteboul/diabetes-health-indicators-dataset-notebook

Primary objectives

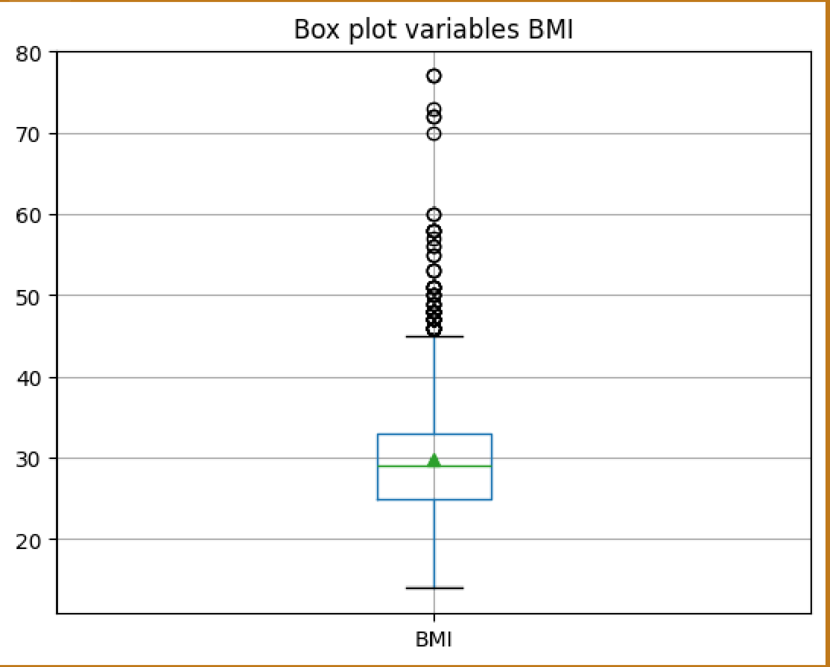
- Classify if person has diabetes
- Compute 5 different methods
    - Comparison
- Reliability of results

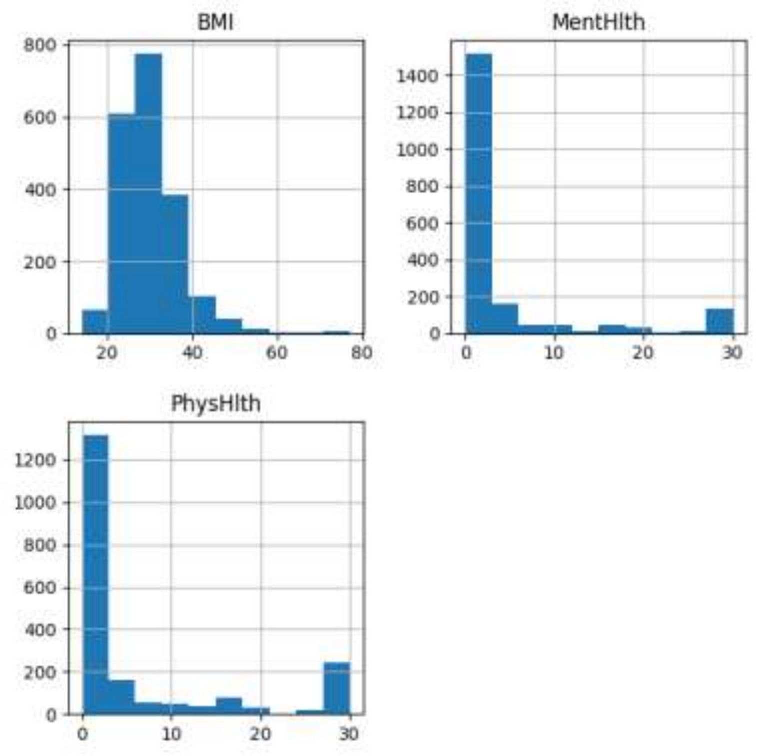
2. Preprocessing

Preprocessing steps

- Randomly select 2000 samples
    - 1000 each type
- Shortening names
    - simplicity
- Uni-variate descriptive
- Outlier detection and substitution

Uni-variate descriptive

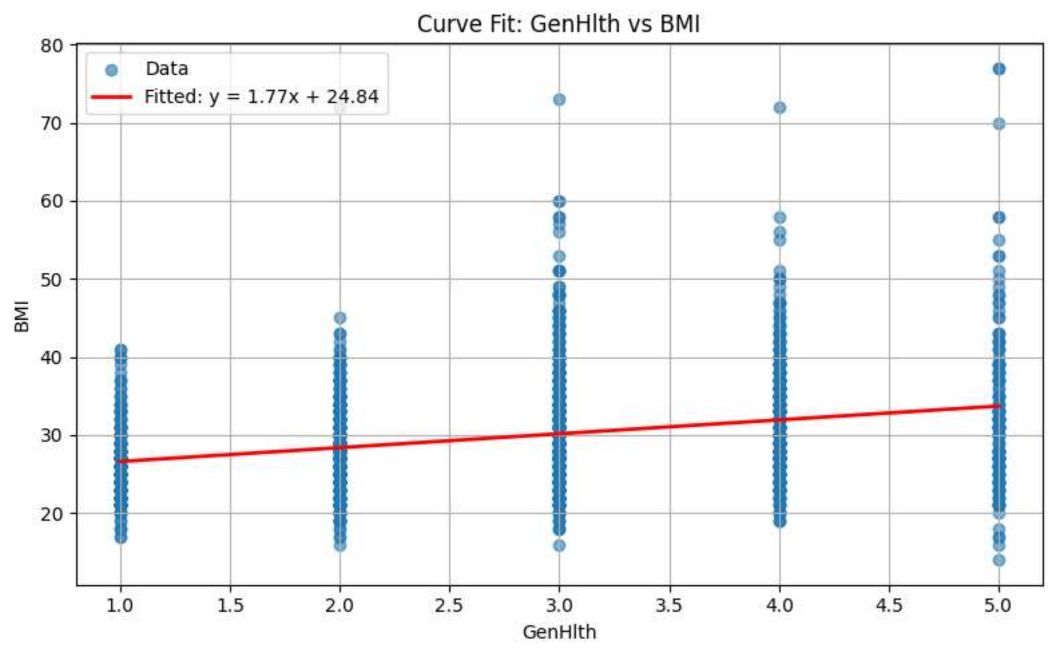




- Outliers?
  - BMI over 70

Outliers treatment

- Bi-variate analysis
- Linear regression
  - two correlated variables
- Outlier detection
  - normal distribution
- Outlier substitution
  - predicted value



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Remaining steps

- **No missing values**
- **No text - categorical variables**
  - one-hot encoding not needed
- **No unnecessary variables**
- **Normalization not needed**
  - mostly boolean and qualitative variables

3. Evaluation criteria of data mining models

Splitting procedure

- Only once for all, right at the start
- Random_state=42 for repeatability
- Stratified sets of data (*stratify=y*)
- 70/30 split

Evaluation methods

- Mainly accuracy and f1-score
  - General indication of quality
- Focus on recall could have been good
  - Health issue
  - Not quite as dangerous as others

	precision	recall	f1-score	support
0.0	0.70	0.75	0.72	1000
1.0	0.73	0.68	0.70	1000
accuracy			0.71	2000

This example comes from Naive Bayes

Cross validation sets

- Each algorithm decides
  - Still using same test / train split
- Generally 10, varies to 5 and 20
- Depends on needs of algorithm

4. Execution of different machine learning methods

a. Naive Bayes - Methodology & Results

Decision Threshold Tuning

- Only hyperparameter used: Decision Threshold (default: 0.5).
- If probability ≥ threshold → classified as positive (diabetes).
- 20-Fold Cross val to identify best threshold, then averaged

Performance Comparison

Default:

- 72% accuracy
- 72% average f1-score

Threshold found:

- 73% accuracy
- 72.5% average f1-score

a. Naive Bayes - Limitations & Discussion

Independence Assumption

- Naive Bayes assumes feature independence
- Health indicators, like BMI or blood pressure, are often correlated
- Weakens the results as the hypothesis is not respected

Dataset Size Consideration

- Dataset: 1000 samples per class (balanced).
- Continuous features:
  - Estimating Gaussian distributions for each feature/class combo
  - 1000 sample may be too few

b. K-NN

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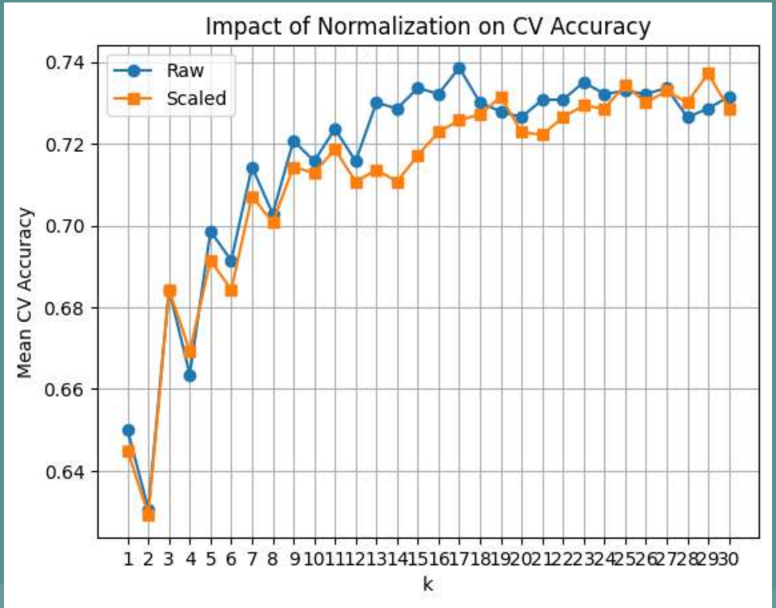

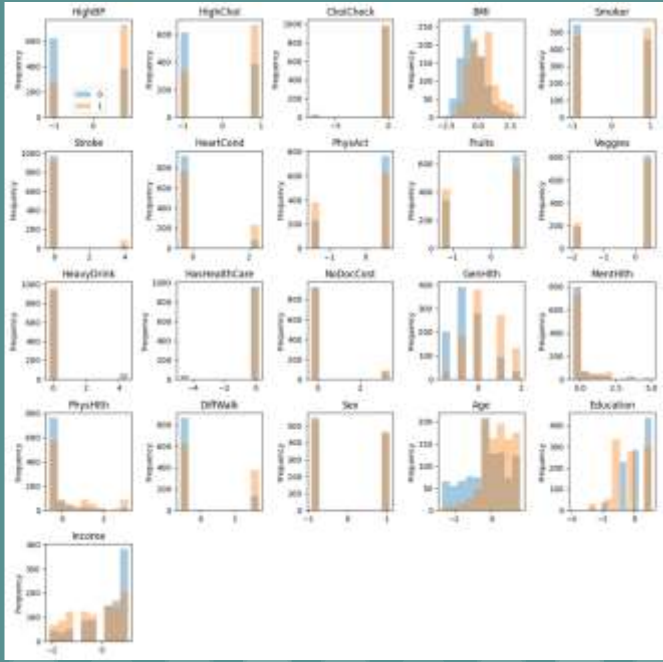

b. K-NN

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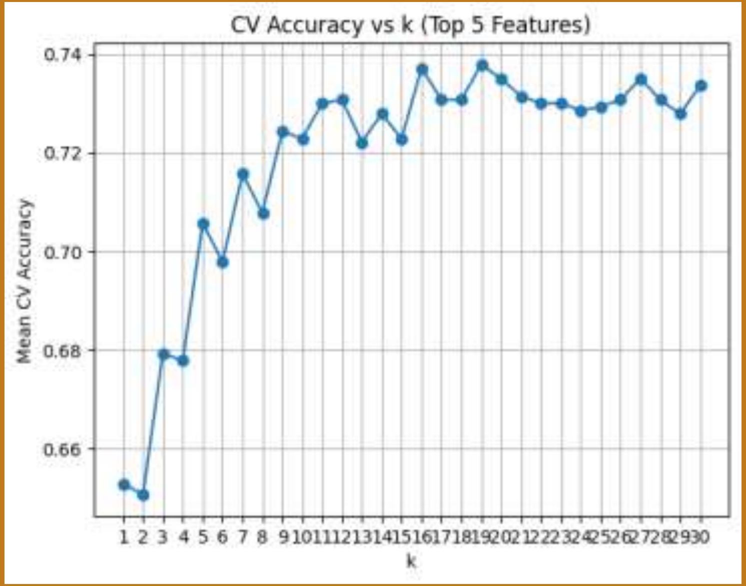
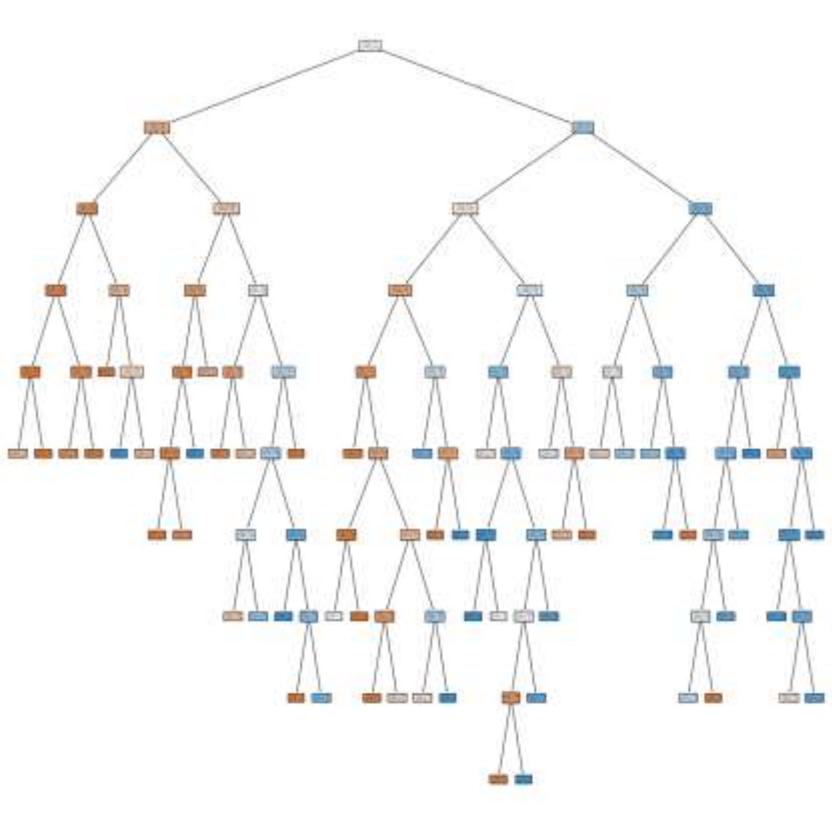



```
Metric=euclidean, weight=uniform, CV acc=0.7371
Metric=euclidean, weight=distance, CV acc=0.7407
Metric=manhattan, weight=uniform, CV acc=0.7314
Metric=manhattan, weight=distance, CV acc=0.7293
Metric=chebyshev, weight=uniform, CV acc=0.6686
Metric=chebyshev, weight=distance, CV acc=0.6736
```

c. Decision Trees

- *DecisionTreeClasifier*
  - hyperparameters
    - criterion: “entropy”
    - min_samples_split
    - min_impurity_decrease

- <u>Initial results</u>
  - big depth >10
  - large number of nodes >50
  - not interpretable
  - low accuracy - 67%

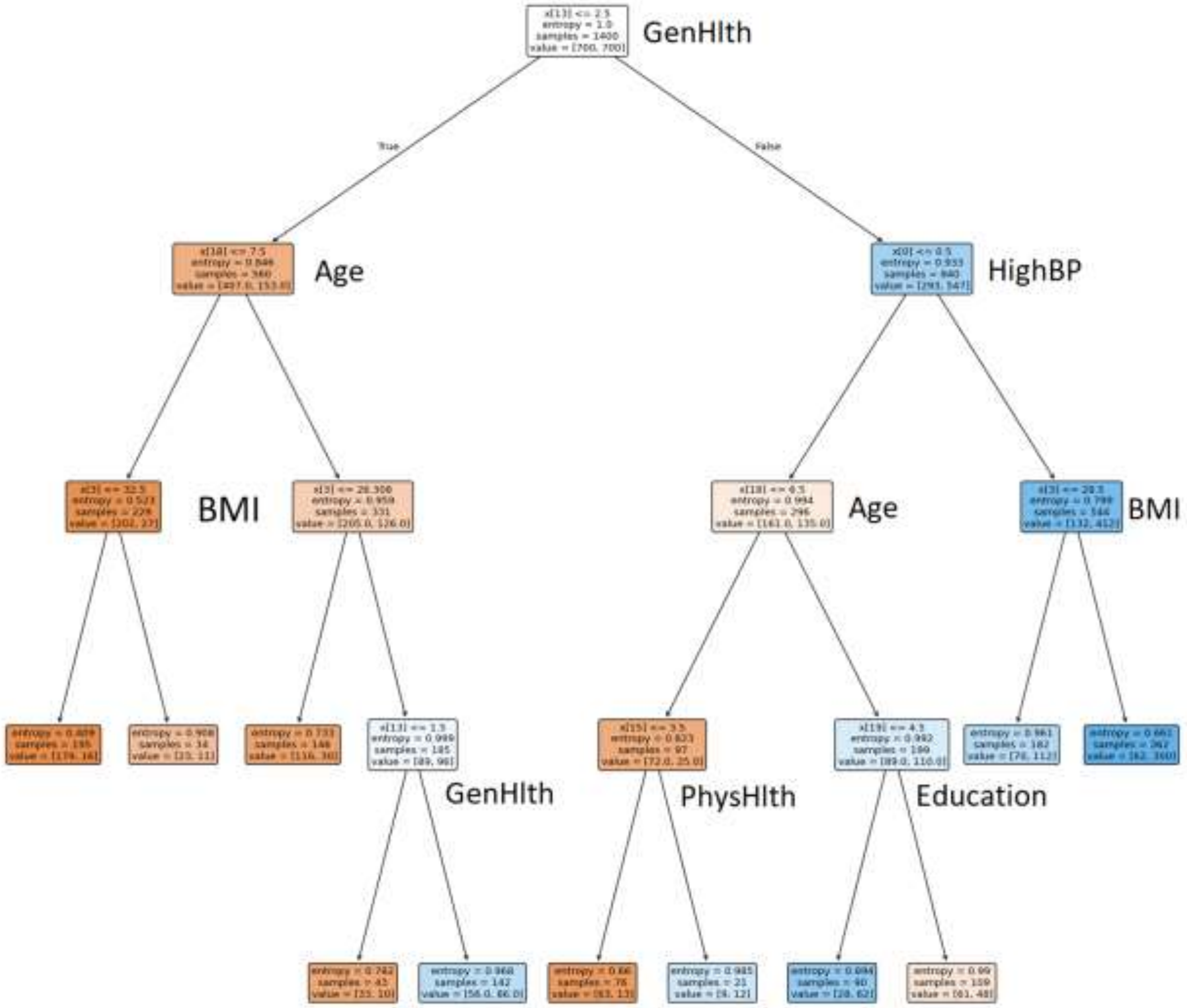


c. Decision Trees

- Grid search
  - min_samples_split
    - 2 to 20, step = 4
  - min_impurity_decrease
    - 0 to 0.05, step = 200

- Obtained hyperparameters
  - min_samples_split - 2
  - min_impurity_decrease - 0.005025

- Improved results
  - smaller depth - 4
  - smaller number of nodes - 21
  - interpretable
  - larger accuracy - 72%



- **True Positive**
  - GenHlth ≤ 2.5 → (value: 2.0)
  - Age > 7.5 → (value: 9.0)
  - BMI > 26.31 → (value: 33.0)
  - GenHlth > 1.5 → (value: 2.0)

- BMI - common rule
- Purity of leaves
  - ideally 100%
- Errors
  - impure leaves (50%/50%)

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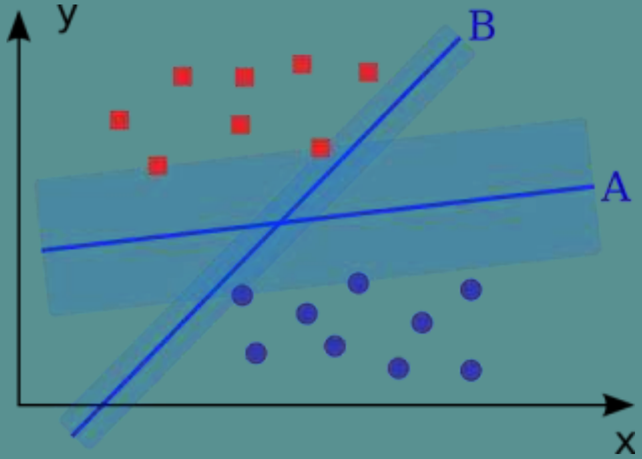
d. Support Vector Machines

- Tested 3 kernels: Linear, Polynomial, RBF
- Balanced dataset, standardized preprocessing
- Two-step model selection for polynomial & RBF:
    - Step 1: Wide scan with 10-fold CV, log-spaced C, max_iter=100000
    - Step 2: Zoom in on best C zone, remove iteration cap
- Dataset row reduction & scaling to speed training



d. Support Vector Machines

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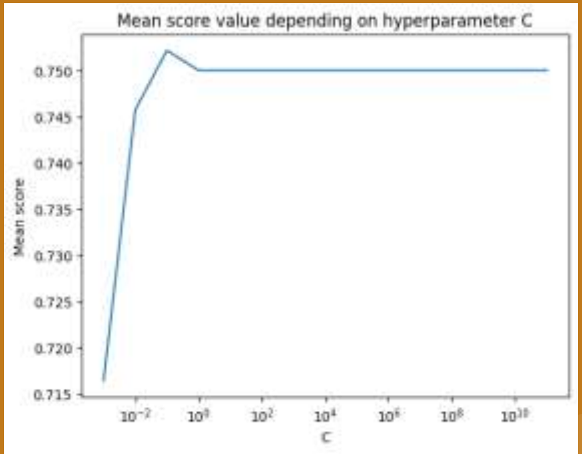
Linear Kernel



Parameters

- Used LinearSVC() for faster training
- Full C grid: logspace(-3, 11, 15)

Results

- Best C = 0.1 → 74.9% CV accuracy, 75.2% test accuracy
- Precision (class 1): ~73%, 76% average f1-score
- 846 support vectors (~60% of training set)

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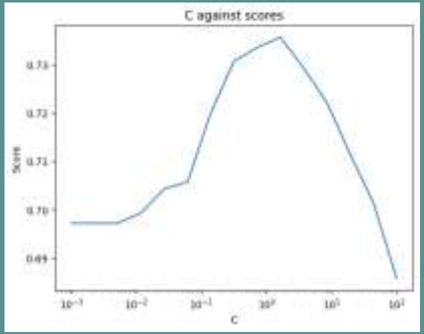
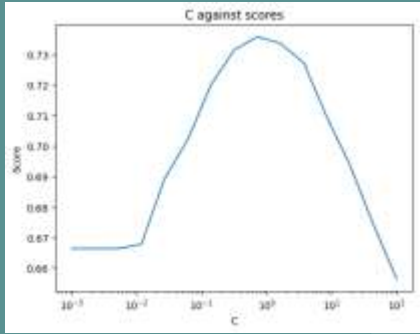
Polynomial Kernel

Parameters



Used two-step training with 10-fold CV



Results Quadratic

Best C ≈ 1.64 → 73.6% CV, 73% test accuracy

851 supports (754 slack)

Results Cubic

Best C ≈ 0.72 → 73.6% CV, 73.5% test accuracy

932 supports (764 slack)

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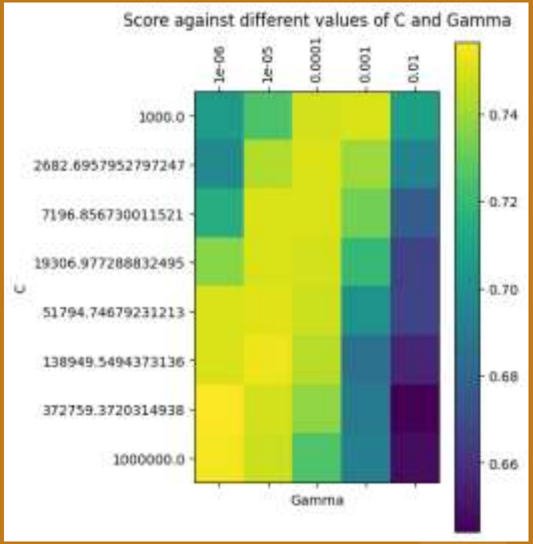
d. Support Vector Machines

RBF Kernel



Parameters

- Two-step grid search on C and gamma
- Step 1: C ∈ [0.1, 10^6], gamma ∈ [10^{-6}, 10], with iteration cap
- Step 2: narrowed region, no iteration cap

Results

- Best C ≈ 3.7×10^5, gamma = 10^{-6}
- 75.6% CV accuracy, 75.7% test accuracy
- Highest accuracy, highest complexity

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e. Meta-learning algorithms

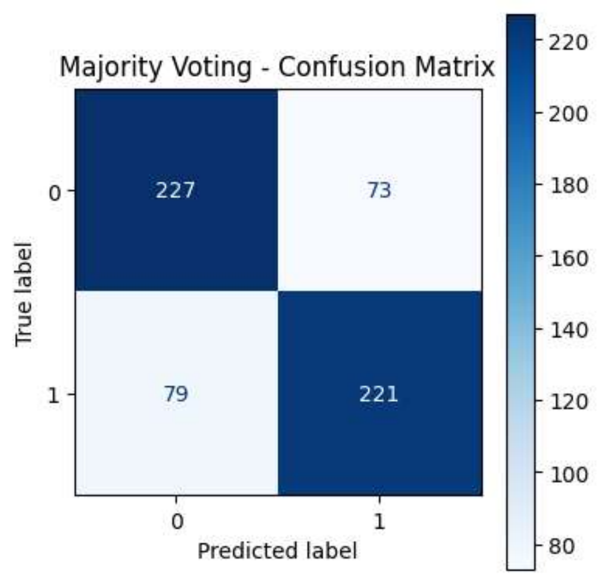
Majority Voting

Parameters

- Hard voting with Naive Bayes, tuned K-NN and a Decision Tree
- 50-fold CV
- Unweighted voting

Results

- Train CV Accuracy: 0.715 [Naive Bayes]
- Best Params fo Knn: {'n_neighbors': 21, 'weights': 'uniform'} - Accuracy: 0.743
- Train CV Accuracy: 0.731 [Knn (3)]
- Train CV Accuracy: 0.660 [Dec. Tree]
- Train CV Accuracy: 0.729 [Majority Voting]



e. Meta-learning algorithms

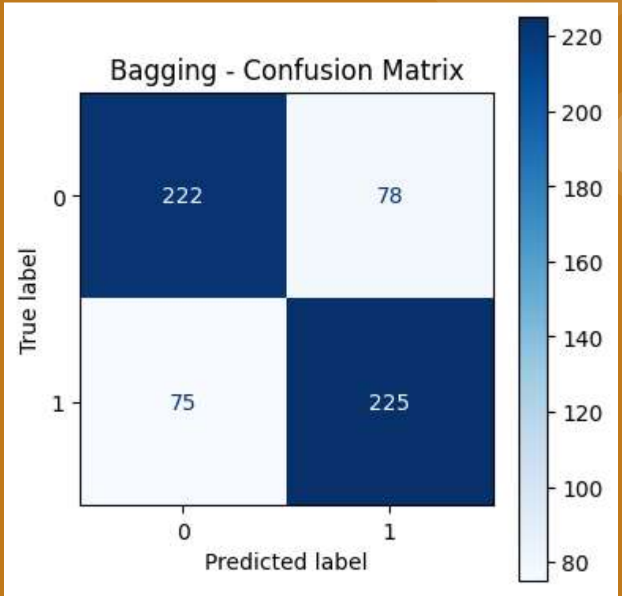
Bagging

Parameters

- Base estimator: Decision Tree
- Max features: 0.35
- 10-fold CV

Results

- Accuracy: 0.629 [n° estimators: 1]
- Accuracy: 0.721 [n° estimators: 50]
- Accuracy: 0.720 [n° estimators: 100]
- **Accuracy: 0.732 [n° estimators: 200]**



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e. Meta-learning algorithms

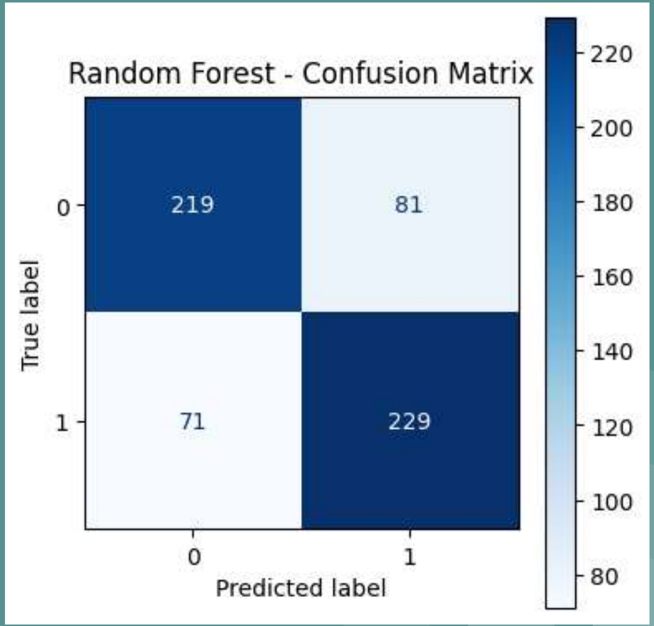
Random Forest

Parameters

- 10-fold CV

Results

- Accuracy: 0.644 [nº estimators (trees): 1]
- Accuracy: 0.726 [nº estimators (trees): 50]
- Accuracy: 0.728 [nº estimators (trees): 100]
- Accuracy: 0.741 [nº estimators (trees): 200]



e. Meta-learning algorithms

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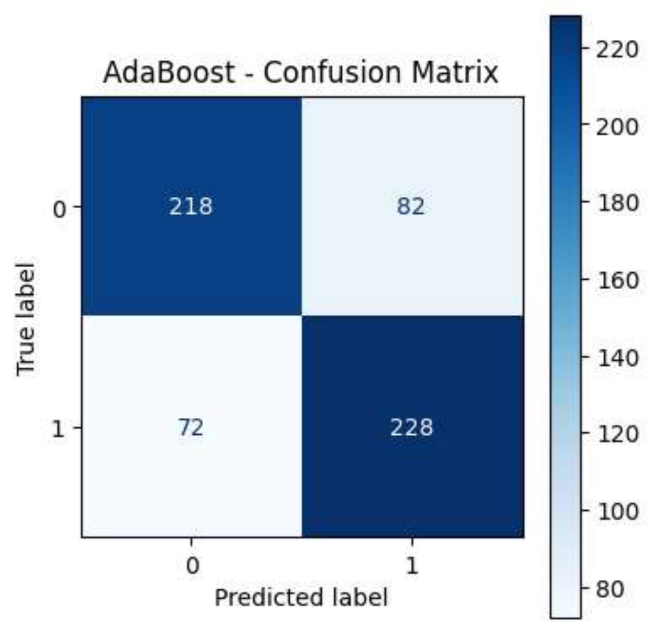
AdaBoost

Parameters

- ???

Results

- Accuracy: 0.668 [nº estimators: 1]
- Accuracy: 0.734 [nº estimators: 50]
- Accuracy: 0.733 [nº estimators: 100]
- Accuracy: 0.736 [nº estimators: 200]



5. Comparison and conclusions

Final conclusions

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Method	**CV Accuracy**	**95% CI**
Naive Bayes (threshold tuned)	73%	68% - 78%
K-NN (k=16, top 5 features)	75%	70.3% - 80.1%
Decision trees (depth 4, pruned)	72%	66.9% - 77.1%
Linear SVM (C = 0.1)	74.9%	70.3% - 80.1%
Polynomial kernels	73.6%	68.3% - 78.9%
RBF SVM ($C \approx 3.7\times10^{5}$, $\gamma = 1\times10^{-6}$)	75.7%	70.8% - 80.6%
Majority Voting	72.9%	67.9% - 77.9%
Bagging (200 trees)	73.2%	68.2% - 78.2%
Random forest (200 trees)	74.1%	69.1% - 79.1%
AdaBoost (200 estimators)	73.6%	68.6% - 78.6%

Questions