MARMARA UNIVERSITY
FACULTY OF ENGINEERING

CSE4062 – S25

Data Science Project Final Delivery
Final Report

Car Price Prediction System

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Project Description

For this project, we selected a dataset containing car listings with various attributes from Kaggle, the owner of our dataset is wspirat and the dataset has an usability of 9.41 with 39 upvotes. This dataset includes data for vehicles manufactured between 1995 and 2023 and contains core attributes such as brand, model, color, fuel type, engine power, transmission type, price, mileage, and more.

We chose this dataset because:

- It provides a diverse set of features suitable for both regression and classification tasks.
- Predicting car prices is a real-world problem with practical applications.
- The subject is appropriate for computer science, engineering, and mechanical engineering and industrial engineering.
- The dataset is large enough (251,078 records) to train and test models effectively.

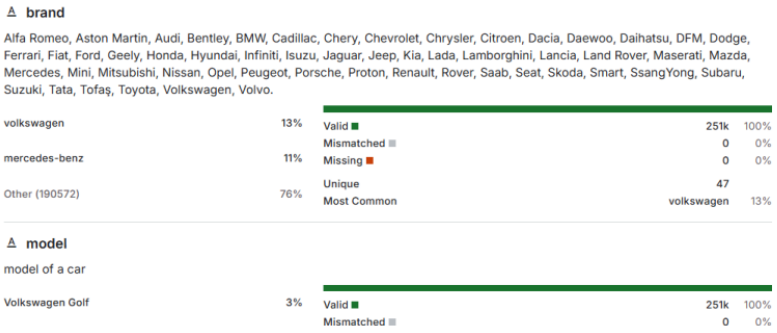
Dataset Statistics

This dataset includes 251,078 rows and 15 columns including index columns. Each row represents a unique car offer with various attributes related to vehicle specifications and market data.

Some statistics and overview about our dataset:

# index	brand: Alfa Romeo, Aston Martin, Audi, Bentley, BMW, Cadillac, Chery, Chevrolet, Chrysler, Citroen, Dacia, Daewoo,	model: model of a car	color: color of the car	registration_date: month, year
0 – 251k	volkswagen 13% mercedes-benz 11% Other (190572) 76%	Volkswagen Golf 3% Opel Astra 2% Other (239127) 95%	black 23% grey 19% Other (145573) 58%	1995-01-01 – 2023-11-01
0	alfa-romeo	Alfa Romeo GTV	red	10/1995
1	alfa-romeo	Alfa Romeo 164	black	02/1995
2	alfa-romeo	Alfa Romeo Spider	black	02/1995
3	alfa-romeo	Alfa Romeo Spider	black	07/1995

# year: year of production from 1995 to 2023	# price_in_euro: price	# power_kw	# power_ps	transmission_type: transmission type manual, semi automatic or automatic
1995 – 27.4k	120 – 5.89m	1 – 2023	1 – 2022	Automatic 52% Manual 47% Other (1461) 1%
1995	1300	148	201	Manual
1995	24900	191	260	Manual
1995	5900	110	150	Unknown
1995	4900	110	150	Manual



The features, their data types (general) and their description:

Feature	Type	Description
brand	Nominal	The brand or manufacturer of the car
model	Nominal	The specific model of the car
color	Nominal	The color of the car's exterior
registration_date	Date	The registration date in MM/YYYY format
year	Numeric	The year of production
price_in_euro	Numeric	The price of the car in Euros
power_kw	Numeric	Numeric Power of the car in kilowatts
power_ps	Numeric	Power of the car in horsepower
transmission_type	Nominal	The type of transmission (e.g., Manual, Automatic)
fuel_type	Nominal	Type of fuel the car uses (e.g., Petrol, Diesel)
fuel_consumption_l_100 km	Text	Fuel consumption in liters per 100 km
fuel_consumption_g_km	Text	CO_2 emissions in grams per km
mileage_in_km	Numeric	Distance the car has traveled in kilometers
offer_description	Text	Free-text description of the offer

Preprocessing

For preprocessing we converted all objects to numeric values and filled in all NaN values by their mean or by their median values. After we accomplished that, we have reduced the number of unique values so that the prediction that can be made would be easier and more precise.

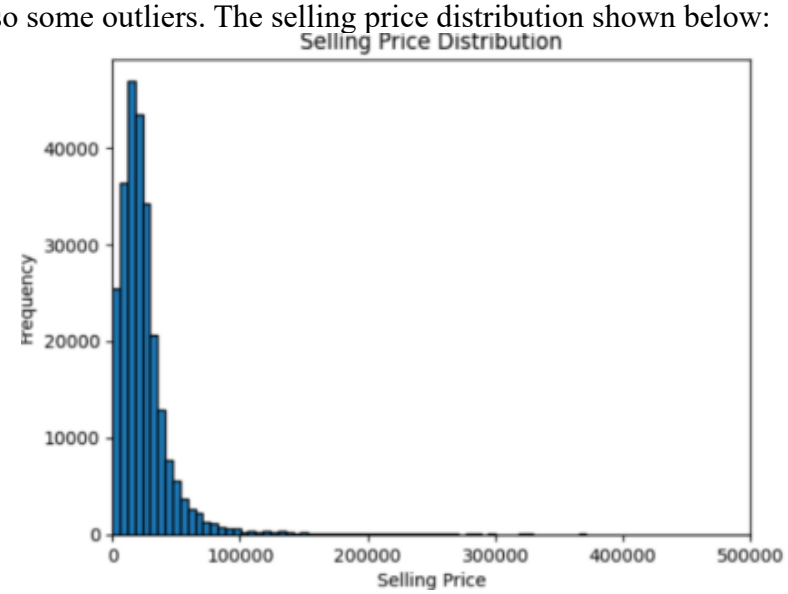
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 251079 entries, 0 to 251078
Data columns (total 15 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   Unnamed: 0              251079 non-null  int64
 1   brand                   251079 non-null  object
 2   model                   251079 non-null  object
 3   color                   250913 non-null  object
 4   registration_date       251075 non-null  object
 5   year                    251079 non-null  object
 6   price_in_euro           251079 non-null  object
 7   power_kw                250945 non-null  object
 8   power_ps                250950 non-null  object
 9   transmission_type       251079 non-null  object
 10  fuel_type               251079 non-null  object
 11  fuel_consumption_l_100km  224206 non-null  object
 12  fuel_consumption_g_km   251079 non-null  object
 13  mileage_in_km           250927 non-null  float64
 14  offer_description       251078 non-null  object
dtypes: float64(1), int64(1), object(13)
memory usage: 28.7+ MB
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 251079 entries, 0 to 251078
Data columns (total 12 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   year                    251079 non-null  float64
 1   price_in_euro           251079 non-null  float64
 2   power_kw                251079 non-null  float64
 3   power_ps                251079 non-null  float64
 4   fuel_consumption_l_100km  251079 non-null  float64
 5   fuel_consumption_g_km   251079 non-null  float64
 6   mileage_in_km           251079 non-null  float64
 7   color_encoded           251079 non-null  int64
 8   brand_encoded           251079 non-null  int64
 9   model_encoded           251079 non-null  int64
 10  fuel_type_encoded       251079 non-null  int64
 11  transmission_type_encoded  251079 non-null  int64
dtypes: float64(7), int64(5)
memory usage: 23.0 MB
```

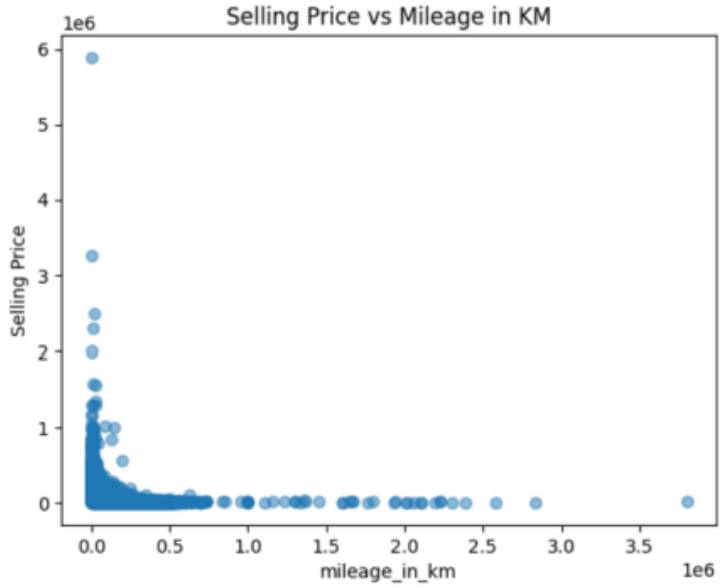
```
Unique values
brand: 6
model: 6
color: 6
year: 33
price_in_euro: 18081
power_kw: 512
power_ps: 521
transmission_type: 4
fuel_type: 6
fuel_consumption_l_100km: 268
fuel_consumption_g_km: 492
mileage_in_km: 71767
```

Analysing the Data

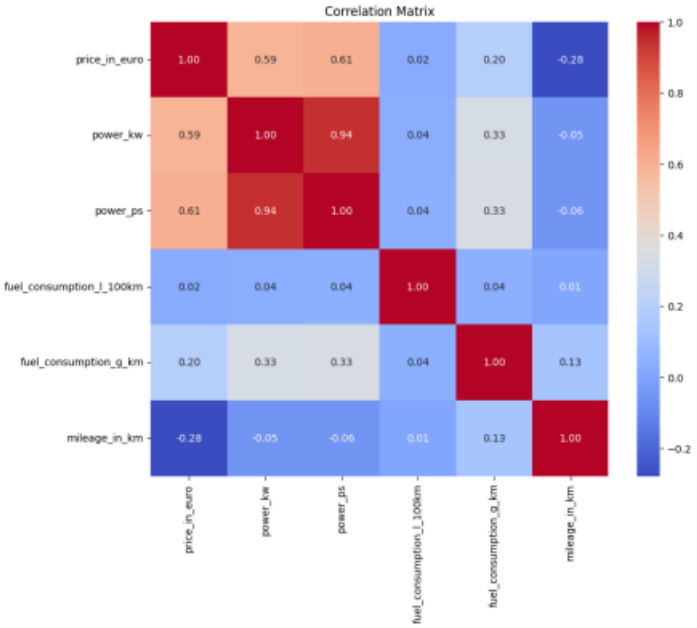
We see in our data that most cars range between the costs of 1000 and 50000 euros. While there are also some outliers. The selling price distribution shown below:



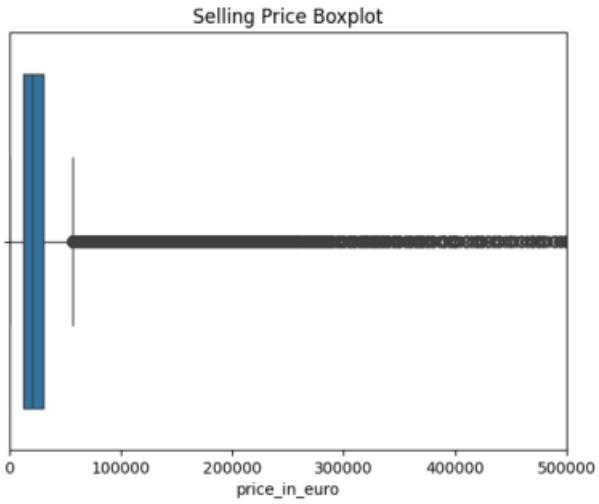
To understand what the prices are based on we made a scatterplot between the columns 'price_in_euro' and 'mileage_in_km'. In here we can see that the prices of cars which has a higher odometer are lower compared to those with a lower odometer.



The correlation matrix can only be obtained by numeric values. So, we created the matrix and realized that 'power_ps' and 'power_kw' are strongly correlated, while 'milage_in_km' and 'price_in_euro' are negatively correlated. Below I leave the correlation matrix:



Furthermore, we made a boxplot for the selling price. For readability, we ranged the values between 0 and 500000 euros. In the boxplot below we see the that the mean is around 3000 euros and the 3rd quartile around 7000 euros, meaning that there are a lot of outliers:



Clustering

Z-Score Normalization

To ensure all numerical features are on a comparable scale, we applied Z-score normalization to the dataset. First, numeric columns were identified using their data types (e.g., float64, int64). Then, the StandardScaler from the Scikit-learn library was used to standardize these columns. This process transforms the data so that each numeric feature has a mean of 0 and a standard deviation of 1. This normalization is important for distance-based clustering algorithms such as DBSCAN, where varying scales can bias the clustering process. Below is an example of the mean and standard deviation before scaling:

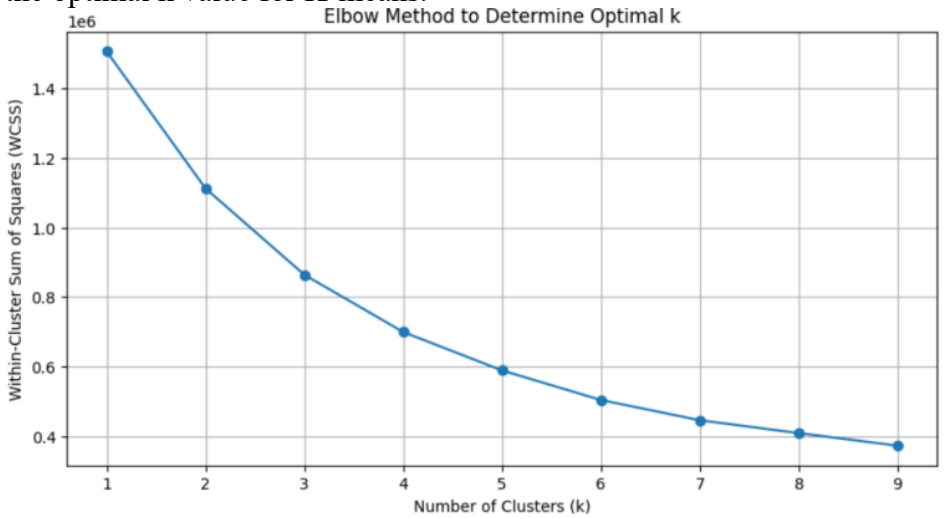
	price_in_euro	power_kw	power_ps	fuel_consumption_l_100km	fuel_consumption_g_km	mileage_in_km
mean	26137.530002	126.477379	171.809526	6.487279	140.802646	85340.015985
std	36973.292968	75.257813	99.150710	26.746251	61.596270	78693.230409

Below are the first five rows showing how the data appears after Z-score normalization. A value of 0 indicates that the data point is at the average, negative values indicate it is below the average, and positive values indicate it is above the average. The larger the absolute value, the further the data point is from the mean, meaning it is more distinct compared to other values. The normalized data table is presented below:

	price_in_euro	power_kw	power_ps	fuel_consumption_l_100km	fuel_consumption_g_km	mileage_in_km
0	-0.671771	0.285986	0.294406	0.164985	1.935143	0.955103
1	-0.033471	0.857356	0.889461	0.000000	0.000000	1.329977
2	-0.547356	-0.218946	-0.219964	0.000000	0.000000	0.554814
3	-0.574403	-0.218946	-0.219964	0.112641	1.366926	1.323623
4	-0.221445	0.073383	0.072521	0.026648	0.000000	0.137077

K-Means Clustering and Elbow Method

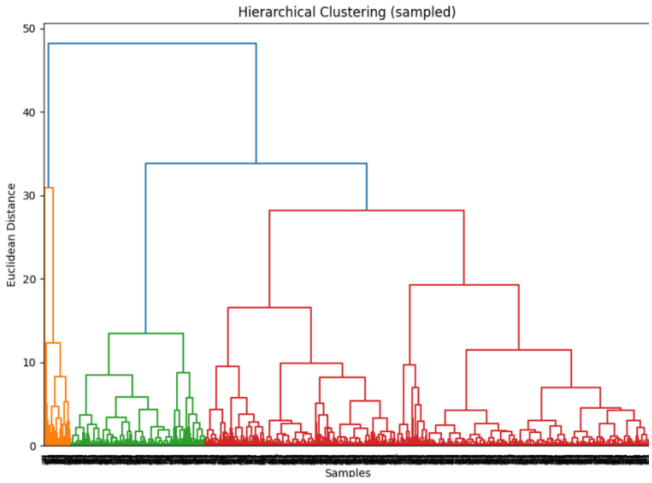
To explore alternative clustering methods beyond DBSCAN, we also applied K-means clustering. To determine the optimal number of clusters (k), the Elbow Method was used. This technique involves plotting the Within-Cluster Sum of Squares (WCSS) against various values of k and identifying the point where the rate of decrease sharply changes. We standardized the dataset using StandardScaler prior to clustering to ensure that all features contribute equally to the distance calculations. The elbow plot shown below suggests a clear bend, which can be interpreted as the optimal k value for K-means.



The graph shows us that how WCSS changes in number of clusters. The bigger number of clusters means the smaller WWCS. As seen from 1 cluster to 2 clusters WWCS decreases sharply.

Hierarchical Clustering Analysis

In addition to Z-Score and K-means, we studied Hierarchical Clustering to visualize the relationships between data points in a tree-like structure called a dendrogram. Due to computational complexity, we randomly sampled 1,000 rows from the normalized dataset. The ward linkage method was chosen because it minimizes the variance within each cluster during the merging process. The dendrogram below represents the distances (using Euclidean distance) between merged clusters and helps reveal the number of natural groupings in the data.

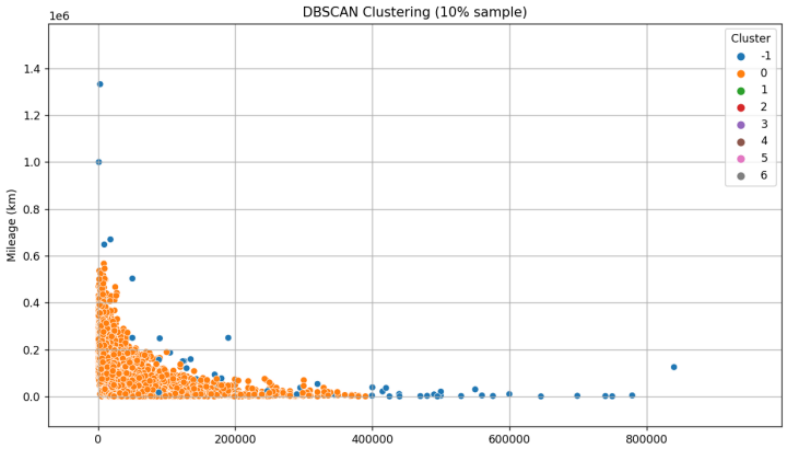


DBSCAN

The aim of this analysis is to identify descriptive patterns in vehicle-related data that can help in understanding customer or product segments. Using DBSCAN (Density-Based Spatial Clustering of Applications with Noise), we explore clusters in a 10% sampled dataset (~25,000 rows) with numerical attributes such as price, power, mileage, year, and fuel consumption

Methodology

1. Data Cleaning
    a. Non-numeric characters (e.g., commas in fuel consumption) were cleaned.
    b. Columns like price_in_euro, power_kw, mileage_in_km, and year were converted to numeric types.
    c. Missing values were imputed using column means.
2. Sampling
    a. A 10% random sample was taken from the full dataset to reduce computational cost while preserving representativeness.
3. Feature Scaling
    a. Features were standardized using StandardScaler to ensure fair distance measurements for DBSCAN.
4. Clustering with DBSCAN
    a. DBSCAN was applied with eps=1.0 and min_samples=5.
    b. The algorithm identified 7 clusters, including noise points (cluster = -1).



```
Cluster counts:
 0    24867
 2      105
-1      101
 6       10
 1        9
 3        6
 5        5
 4        5
Name: cluster, dtype: int64

Cluster-wise mean and median values:
           year         price_in_euro  ... fuel_consumption_l_100km mileage_in_km
           mean  median          mean  ...                   median          mean   median
cluster                                ...
0       2016.27  2018.0      25234.02  ...                      5.7      85417.42  67700.0
1       2021.11  2021.0      27186.22  ...                    316.0      14173.00  11800.0
2       2019.67  2020.0      24846.31  ...                    100.0      40624.23  30300.0
3           NaN     NaN           NaN  ...                      NaN           NaN      NaN
4           NaN     NaN           NaN  ...                   2020.0           NaN      NaN
5       2019.80  2020.0      23654.00  ...                    392.0      24048.40  25500.0
6       2022.00  2022.0      33591.90  ...                    479.0       5459.20   3175.0

[7 rows x 10 columns]
```

Association Rule Mining (ARM)

This analysis applies the Apriori algorithm to extract frequent patterns and asociation rules from a dataset of used vehicles. The objective is to identify meaningful relationships between attributes such as brand, model, transmission type, fuel type, price range, year of production, and mileage. These insights can be useful for strategic business decisions such as pricing, inventory planning, and targeted marketing.

Frequent Pattern Mining

- Apriori algorithm was applied with: o Minimum support: 0.2
- Association rules were then generated with: o Minimum lift threshold: 1.0
- Rules were filtered further to find interesting patterns, defined as:
  o Lift > 1.2
  o Confidence > 0.6

```
 Interesting Apriori Rules:
                 antecedents                 consequents  ...  confidence      lift
2  (transmission_type_Manual)          (fuel_type_Petrol)  ...    0.693864  1.215903
5       (price_range_mid-low)  (transmission_type_Manual)  ...    0.639288  1.361782
```

Another Apriori Method From Reprocessing

To discover meaningful patterns among categorical variables, we applied Association Rule Mining (ARM) again using the Apriori algorithm. First, missing values in categorical features were replaced with 'unknown', and the data was transformed into a list of transactions. Then, one-hot encoding was applied using TransactionEncoder from the mlxtend library to prepare the data for frequent itemset generation.

Frequent itemsets were identified with a minimum support of 0.02, and association rules were generated based on confidence ≥ 0.4. The top 10 rules were then sorted by lift, which measures how much more likely the consequent is given the antecedent than by random chance.

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	representativity	leverage	conviction	zhangs_metric	jaccard	certainty	kulczynski
173	(Volkswagen Golf)	(volkswagen, Petrol)	0.030222	0.072240	0.020631	0.682657	9.449818	1.0	0.018448	2.923522	0.922043	0.252117	0.657947	0.484123
170	(Volkswagen Golf)	(Manual, volkswagen)	0.030222	0.076737	0.020137	0.666315	8.683125	1.0	0.017818	2.766872	0.912408	0.231937	0.638581	0.464366
172	(Volkswagen Golf, Petrol)	(volkswagen)	0.020631	0.132552	0.020631	1.000000	7.544214	1.0	0.017896	inf	0.885721	0.155644	1.000000	0.577822
81	(Volkswagen Golf)	(volkswagen)	0.030222	0.132552	0.030222	1.000000	7.544214	1.0	0.026216	inf	0.894481	0.227998	1.000000	0.613999
168	(Volkswagen Golf, Manual)	(volkswagen)	0.020137	0.132552	0.020137	1.000000	7.544214	1.0	0.017468	inf	0.885275	0.151919	1.000000	0.575959
29	(Electric)	(Automatic)	0.023769	0.524731	0.022929	0.964645	1.838360	1.0	0.010456	13.442672	0.467140	0.043627	0.925610	0.504171
30	(Hybrid)	(Automatic)	0.050307	0.524731	0.046619	0.926688	1.766025	1.0	0.020221	6.482850	0.456733	0.088223	0.845747	0.507766
147	(ford, Petrol)	(Manual)	0.041198	0.469450	0.032563	0.790410	1.683694	1.0	0.013223	2.531370	0.423516	0.068112	0.604957	0.429888
130	(mercedes-benz)	(Automatic, Petrol)	0.108436	0.241784	0.043687	0.402887	1.666306	1.0	0.017469	1.269802	0.448504	0.142521	0.212476	0.291787
153	(opel)	(Manual, Petrol)	0.081202	0.325846	0.044026	0.542182	1.663922	1.0	0.017567	1.472537	0.434274	0.121277	0.320900	0.338647

The interesting thing that observed is that if a car is Volkswagen Golf, then it is likely to be Petrol, Lift = 9.44 and Confidence = 0.68. Also the confidence of electric car is automatic is 0.96, confidence of hybrid car is automatic is 0.92. These are pretty high confidence scores. However the list is ascending by lift, so that it is not shown in the first row

Feature Selection

#	Feature Name	Description	Type	Mutual Information	Lasso	Information Gain
1	year	The manufacturing year of the vehicle	float64	0.5214	0.0325	0
2	price_in_euro	The price of the car in euros	float64	-	-	0.0964
3	power_kw	Engine power measured in kilowatts	float64	0.5944	0.1327	0.1404
4	power_ps	Engine power measured in horsepower	float64	0.5913	0.4306	0.0161
5	fuel_ consumption_l_100 km	Fuel consumption in liters per 100 km	float64	0.2521	0.0042	0.4075
6	fuel_ consumption_g_km	CO_2 emissions measured in g/km	float64	0.3364	0	0.0954
7	mileage_ in_km	Total distance the car travelled in km	float64	0.4123	-0.7816	0.2199
8	color_ encoded	Numerical enconding shows vehicle's color	int64	0.0447	0.0043	0
9	brand_ encoded	Numerical enconding shows vehicle's brand	int64	0.0826	0	0.0006
10	model_encoded	Numerical enconding shows vehicle's specific model	int64	0.04	0.068	0
11	fuel_type_ encoded	Numerical enconding shows type of fuel used	int64	0.0809	-0.2642	-
12	transmission_type_ encoded	Numerical enconding shows transmission type	int64	0.179	-0.2953	0.0238

In this section, feature importance was evaluated using three methods: Mutual Information, Lasso Regression, and Information Gain. These techniques helped identify which features were most relevant for predicting car prices. Features like power_kw, mileage_in_km, and fuel_consumption_l_100km consistently showed high importance. The results guided the selection of features used in regression and classification models, improving overall model performance.

Classification/Regression Experiments

Regression Results

In order to build an effective regression model for predicting the price_in_euro attribute, we employed both Artificial Neural Networks (ANN) and Support Vector Regression (SVR). Since the original dataset was large, we randomly sampled 20,000 instances to reduce training time and computational cost while maintaining representative data diversity.

Artificial Neural Network (ANN) Report

In this experiment, a Multi-Layer Perceptron (MLPRegressor) was used to predict car prices. The network consisted of two hidden layers with 128 and 64 neurons respectively. The ReLU activation function and Adam optimizer were selected to enhance training performance and convergence speed.

Model Performance

Fold	MAE (EUR)	MSE	MAPE (%)	R^2
Fold 1	5,573.27	472,265,695.91	23.29	0.5824
Fold 2	5,041.16	200,030,655.42	18.94	0.7136
Fold 3	8,511.94	18,136,295,589.53	32.49	-18.6107
Fold 4	5,343.15	233,675,050.26	19.67	0.7384
Fold 5	5,593.38	333,170,020.30	22.25	0.6657
Fold 6	5,413.65	174,991,126.19	21.73	0.8170
Fold 7	5,866.15	367,202,949.15	23.24	0.7388
Fold 8	6,004.98	428,694,715.70	19.66	0.6816
Fold 9	7,258.86	6,084,609,544.80	28.17	-4.8285
Fold 10	5,269.67	189,381,649.27	21.30	0.7871

The ANN model exhibited generally good performance in most folds, with MAE values typically ranging from €5,000 to €6,000 and R^2 scores above 0.65, suggesting solid predictive ability. The best performance was seen in Fold 6 ($R^2 = 0.8170$), while Folds 3 and 9 significantly underperformed, with very high MSE values and negative R^2 scores. These outliers likely stem from the presence of extreme values or variance in the validation sets.

Despite the two poor-performing folds, the overall results indicate that the ANN model is effective for car price prediction, especially with additional data cleaning or robust training techniques to mitigate outlier effects.

Support Vector Regression (SVR) Report

Model Description

Support Vector Regression (SVR) with a Radial Basis Function (RBF) kernel was employed to predict car prices. The model was configured with a penalty parameter C=100 and an epsilon-insensitive tube of epsilon=0.1. SVR is known for its robustness in handling non-linear regression tasks, especially with smaller or moderately sized datasets.

Model Performance

Fold	MAE (EUR)	MSE	MAPE (%)	R^2
Fold 1	5,149.45	437,033,862.14	22.77	0.6136
Fold 2	5,387.02	276,578,977.98	20.33	0.6041
Fold 3	5,113.87	299,758,512.47	19.60	0.6759
Fold 4	5,066.59	367,001,266.81	18.86	0.5892
Fold 5	5,109.73	237,807,494.38	20.21	0.7614
Fold 6	5,092.61	162,083,205.46	19.49	0.8305
Fold 7	5,187.10	325,472,701.76	20.77	0.7685
Fold 8	5,053.72	167,762,093.93	19.53	0.8754
Fold 9	4,929.36	179,570,140.36	20.02	0.8280
Fold 10	5,343.33	285,210,242.85	20.65	0.6794

The SVR model demonstrated consistent and reliable performance across all folds, with MAE values tightly clustered around €5,000 and R^2 scores mostly above 0.65. The model showed especially strong results in Folds 6, 8, and 9, achieving R^2 scores above 0.82, indicating a high level of explained variance.

Unlike the ANN model, SVR did not suffer from extreme outliers or negative R^2 values, suggesting better generalization and robustness. This consistent behavior indicates that SVR is well-suited for the car price prediction task, especially when stability across folds is a priority.

Comparison of ANN and SVR Models

To build a regression model for predicting car prices, we employed two approaches: Artificial Neural Networks (ANN) and Support Vector Regression (SVR). Due to the large size of the original dataset, a sample of 20,000 instances was used to reduce training time. Both models were evaluated using 10-fold cross-validation, and their performance metrics—MAE, MSE, MAPE, and R^2—were compared.

Metric	ANN (Mean)	SVR (Mean)
MAE	5,587.82	5,134.88
MSE	2.71e+09	2.74e+08
MAPE	23.00%	20.02%
R^2	0.58	0.72

SVR consistently outperformed ANN with lower errors (MAE, MSE, MAPE) and higher R^2 values, indicating better predictive accuracy and model stability.

Statistical Significance Test

A paired t-test was conducted on the MAE values across the 10 folds to determine if the performance difference between ANN and SVR is statistically significant.

- t-statistic: 2.3193
- p-value: 0.0455

Since the p-value is less than 0.05, we reject the null hypothesis and conclude that the difference in MAE between ANN and SVR is statistically significant. This confirms that SVR performs significantly better than ANN on this dataset.

Classification Results

We have made for **3 models**, Naïve Bayes, K-NN, and Random Forest Tree, **3 predictions**, making it a total of **9 experiments**.

The code performs binning operations on three numerical features — price_in_euro, mileage_in_km, and year — to convert them into categorical variables suitable for classification tasks. Here's a breakdown of the steps:

1. **Price Binning**:

   The price_in_euro column is divided into five ranges: Very Low, Low, Medium, High, and Very High, using specified thresholds. This creates a new categorical column called price_category. Any rows with missing values in this new category are dropped to ensure data integrity.

2. **Mileage Binning**:

   The mileage_in_km column is similarly binned into three categories: Low, Medium, and High, based on its value range. The resulting column, mileage_in_km_category, replaces the numerical feature for classification purposes. Again, rows with missing values in this new column are removed.

3. **Year Binning**:

   The year column is binned into four historical ranges: Before 2000, 2000-2010, 2010-2020, and After 2020, and stored in the year_category column. Rows with missing values in the original year column are dropped.

Feature Selection Using Multiple Methods

The goal is to determine which features are most informative for building a classification model Feature Selection table:

```
Feature Selection Table:
                      Feature                                Description  \
0                        year                        Description of year
1                   power_ps                   Description of power_ps
2                   power_kw                   Description of power_kw
3               mileage_in_km               Description of mileage_in_km
4   transmission_type_encoded  Description of transmission_type_encoded
5       fuel_consumption_g_km      Description of fuel_consumption_g_km
6    fuel_consumption_l_100km   Description of fuel_consumption_l_100km
7           fuel_type_encoded          Description of fuel_type_encoded
8               model_encoded              Description of model_encoded
9               brand_encoded              Description of brand_encoded
10              color_encoded              Description of color_encoded
```

Mutual Information

The mutual_info_classif function calculates the **mutual information** between each feature and the target variable. Mutual information measures the amount of shared information between the feature and the target. Higher values indicate a stronger relationship. It works well with both linear and non-linear relationships.

	Mutual Information
0	0.348771
1	0.296521
2	0.296448
3	0.244958
4	0.136824
5	0.110378
6	0.091430
7	0.047939
8	0.039531
9	0.037592
10	0.018749

Price

	Mutual Information
0	0.290181
1	0.218967
2	0.086794
3	0.072355
4	0.072323
5	0.063662
6	0.049960
7	0.031209
8	0.030748
9	0.025290
10	0.015965

Mileage

Mutual Information
0.458572
0.349177
0.147406
0.145580
0.100761
0.084577
0.070170
0.058187
0.046793
0.031922
0.027305

Year

ANOVA F-value

The f_classif function performs an ANOVA F-test for each feature to check whether the mean of the feature differs significantly across the classes in the target variable. The result is a list of F-values, where a higher F-value means the feature is more discriminative with respect to the classes.

ANOVA F-value
294.257926
42077.457508
38203.913159
33506.477296
17715.514839
3608.738339
51.916958
955.926735
1421.407696
176.954692
154.782685

Price

ANOVA F-value
490.596829
8374.486860
9088.312706
528.435289
517.418479
3758.705879
2223.369261
5.474472
134.101373
795.271099
2052.252255

Mileage

ANOVA F-value
63016.796503
6648.341386
683.429678
653.629825
3710.367359
24.190354
1684.039055
1859.163819
658.838411
198.527889
3205.222883

Year

Random Forest Feature Importance

A Random Forest Classifier is trained using the feature matrix X and encoded labels y_encoded. After training, the feature_importances_ attribute gives the relative importance of each feature based on how useful they were in the decision trees of the ensemble.

RF Importance
0.255503
0.113186
0.121756
0.225946
0.061629
0.066416
0.063269
0.015629
0.010386
0.031050
0.035229

RF Importance
0.248417
0.314409
0.059885
0.052132
0.054235
0.038124
0.083149
0.075526
0.007681
0.051630
0.014812

RF Importance
0.381035
0.270563
0.054557
0.055062
0.064196
0.078244
0.019856
0.031742
0.027904
0.005456
0.011386

Price Mileage Year

Model Definitions

Three classification models are defined:

- **Naive Bayes** (GaussianNB()): A simple probabilistic classifier based on Bayes' theorem.
- **k-Nearest Neighbors (k=5)** (KNeighborsClassifier): A distance-based classifier where each sample is assigned the majority label of its 5 nearest neighbors.
- **Random Forest** (RandomForestClassifier): An ensemble of decision trees trained with bagging and random feature selection for robustness and performance.

Feature Subsets

Feature sets used for training are:

- **All Features**: The full list of features.
- **Top 5 MI Features**: The top 5 features with the highest Mutual Information scores.
- **Top 8 MI Features**: The top 8 based on Mutual Information as well.

This allows testing how models perform when using only the most informative features vs. all features.

Cross-Validation Setup

- **StratifiedKFold (10 splits)**: Ensures that each fold maintains the class distribution (stratification), preventing class imbalance issues in train-test splits.

Evaluation Loop

For **each combination of model and feature subset**:

- The data is split into training and testing sets based on cross-validation folds.
- The model is trained on the training data.
- Predictions are made on the test data.
- The following metrics are computed for each fold:

- **Accuracy**
- **F1 Score (Macro)**: Treats all classes equally.
- **F1 Score (Micro)**: Aggregates contributions of all classes for overall performance.
- **AUC (Area Under Curve)**:
  - For multi-class, One-vs-Rest (OvR) strategy is used.
  - If predict_proba is not available, or the calculation fails, AUC is set to NaN.

Each metric is averaged over all 10 folds to get a robust performance estimate. All 9 results are show below:

```
Classification Experiments Results:
                          Experiment  Accuracy  F1-macro  F1-micro  \
0         Naive Bayes with All Features  0.498556  0.452167  0.498556
1    Naive Bayes with Top 5 MI Features  0.537982  0.485920  0.537982
2    Naive Bayes with Top 8 MI Features  0.498409  0.453210  0.498409
3          k-NN (k=5) with All Features  0.758817  0.634051  0.758817
4     k-NN (k=5) with Top 5 MI Features  0.764210  0.635357  0.764210
5     k-NN (k=5) with Top 8 MI Features  0.758379  0.633816  0.758379
6       Random Forest with All Features  0.882623  0.814855  0.882623
7  Random Forest with Top 5 MI Features  0.814580  0.759090  0.814580
8  Random Forest with Top 8 MI Features  0.867815  0.796301  0.867815

        AUC
0  0.860711
1  0.884247
2  0.860338
3  0.867596
4  0.876645
5  0.867493
6  0.971636
7  0.946391
8  0.964765
```

Price Results

```
Classification Experiments Results:
                          Experiment  Accuracy  F1-macro  F1-micro  \
0         Naive Bayes with All Features  0.345732  0.379833  0.345732
1    Naive Bayes with Top 5 MI Features  0.395899  0.425202  0.395899
2    Naive Bayes with Top 8 MI Features  0.344891  0.377827  0.344891
3          k-NN (k=5) with All Features  0.774103  0.646679  0.774103
4     k-NN (k=5) with Top 5 MI Features  0.782479  0.661056  0.782479
5     k-NN (k=5) with Top 8 MI Features  0.773745  0.645318  0.773745
6       Random Forest with All Features  0.833367  0.744605  0.833367
7  Random Forest with Top 5 MI Features  0.793794  0.689565  0.793794
8  Random Forest with Top 8 MI Features  0.825402  0.733597  0.825402

        AUC
0  0.688875
1  0.727826
2  0.687567
3  0.853536
4  0.862116
5  0.853350
6  0.937034
7  0.905133
8  0.932035
```

Mileage Results

```
Classification Experiments Results:
                          Experiment  Accuracy  F1-macro  F1-micro  \
0         Naive Bayes with All Features  0.493518  0.381785  0.493518
1    Naive Bayes with Top 5 MI Features  0.780240  0.550361  0.780240
2    Naive Bayes with Top 8 MI Features  0.492407  0.380811  0.492407
3          k-NN (k=5) with All Features  0.832336  0.601099  0.832336
4     k-NN (k=5) with Top 5 MI Features  0.832272  0.601037  0.832272
5     k-NN (k=5) with Top 8 MI Features  0.832332  0.601096  0.832332
6       Random Forest with All Features  0.918575  0.820048  0.918575
7  Random Forest with Top 5 MI Features  0.895495  0.741932  0.895495
8  Random Forest with Top 8 MI Features  0.916469  0.816174  0.916469

        AUC
0  0.885176
1  0.870265
2  0.884861
3  0.839185
4  0.839114
5  0.839181
6  0.985632
7  0.965456
8  0.984123
```

Year Results

ROC Curves

To visualize model performance across different classes, we plotted ROC (Receiver Operating Characteristic) curves for each classification model (Naive Bayes, k-NN, and Random Forest) based on a one-vs-rest multi-class strategy.

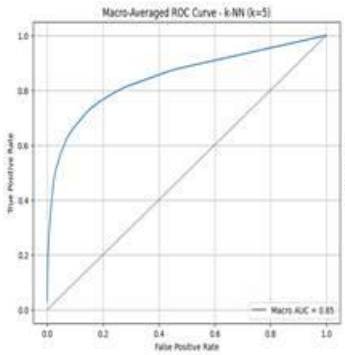
- Only one-fold (the first split) from the cross-validation is used to ensure a fair and consistent comparison.
- The target labels are binarized using the one-vs-rest approach for multi-class ROC analysis. This means for each class, it's treated as the positive class while the rest are negative.
- The predicted probabilities from each model are used to calculate:
    - False Positive Rate (FPR)
    - True Positive Rate (TPR) for each class individually.
- Then, the macro-average ROC curve is computed by averaging the TPR values across all classes for each unique FPR value.
- The macro AUC (Area Under the Curve) is also calculated to represent the overall discriminative ability of the model.

Purpose:

- The goal is to show how well each model can distinguish between classes across all categories, not just the most frequent ones.
- A curve that bows closer to the top-left corner indicates better performance.
- AUC values closer to 1.0 represent high performance, while values closer to 0.5 indicate poor performance (random guessing level).

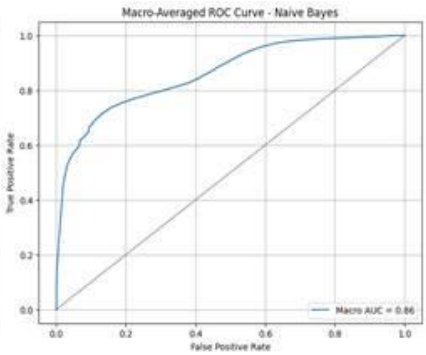
What You See in the Plot:

- A line for the macro-averaged ROC curve of the model.
- A diagonal dashed line which represents random classification (baseline).
- AUC score shown in the legend to compare models visually and numerically.



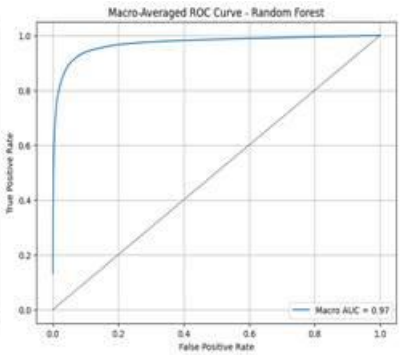
ROC Curve for KNN

(Price Category)



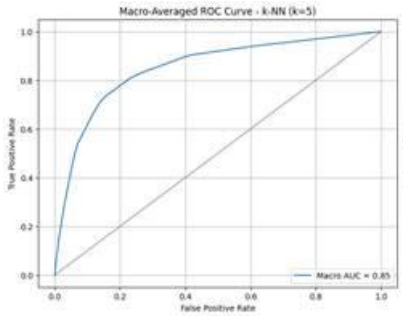
ROC Curve for Naive Bayes

(Price Category)



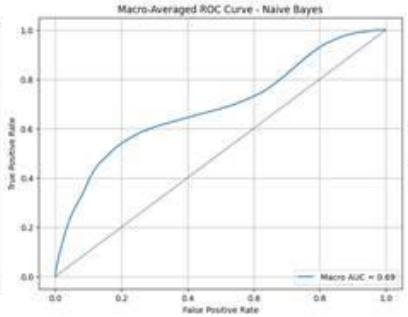
ROC Curve for Random Forest

(Price Category)



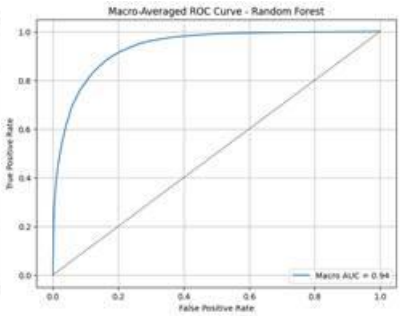
ROC Curve for KNN

(Mileage Category)



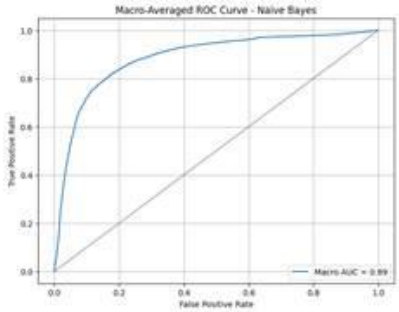
ROC Curve for Naive Bayes

(Mileage Category)



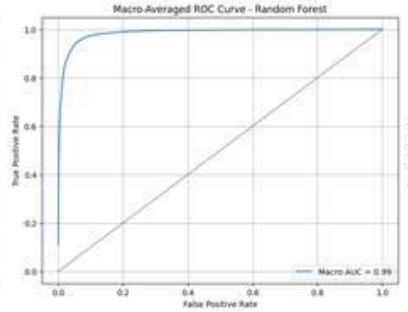
ROC Curve for Random Forest

(Mileage Category)



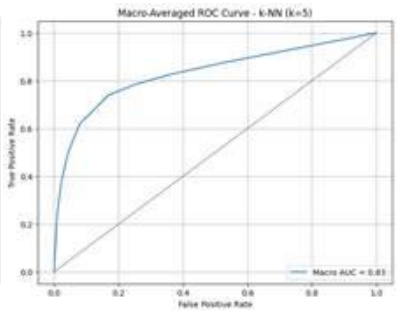
ROC Curve for KNN

(Year Category)



ROC Curve for Naive Bayes

(Year Category)



ROC Curve for Random Forest

(Year Category)

Confusion Matrices

To further analyze the classification performance of our models, we utilized confusion matrices for each task (Price, Mileage, Year) and for each model (Naive Bayes, k-NN, Random Forest) using the best-performing feature subset from the feature selection phase.

Purpose of Confusion Matrix:

A confusion matrix provides a detailed breakdown of model predictions by showing:

- How many instances of each class were correctly classified (true positives on the diagonal).
- How many were misclassified, and to which other classes (off-diagonal elements).

This is extremely useful in understanding:

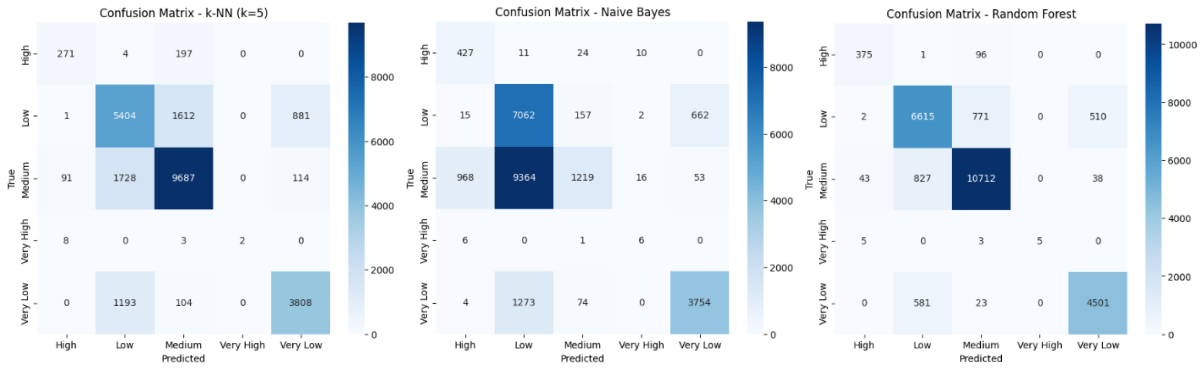
- Which classes are more easily confused with each other.
- Whether the model is biased toward certain classes.

How It Was Done:

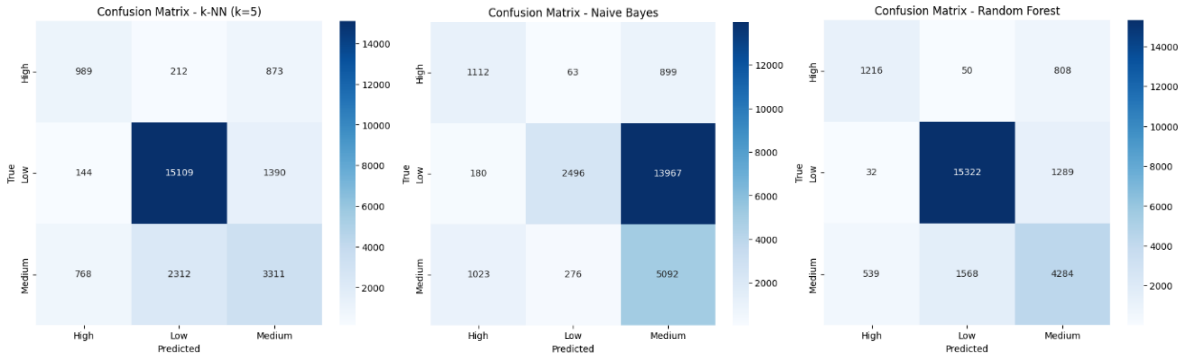
- For each model (Naive Bayes, k-NN, Random Forest), the best feature subset is used (based on earlier feature selection).
- The model is trained on the selected features and then tested on a consistent test set.
- The confusion matrix is computed by comparing the predicted labels to the true labels.
- A heatmap is used to visualize this matrix clearly.

What You See in the Plot:

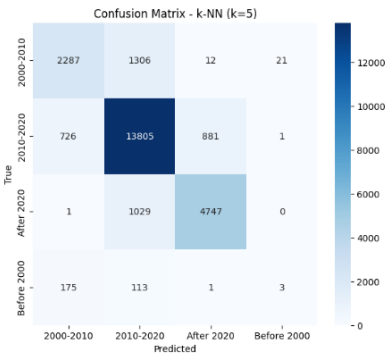
- Rows represent the true class labels.
- Columns represent the predicted class labels.
- Darker or brighter colors indicate higher numbers of instances.
- Diagonal values show the correct classifications.
- Off-diagonal values show which classes were misclassified as which, highlighting model weaknesses.



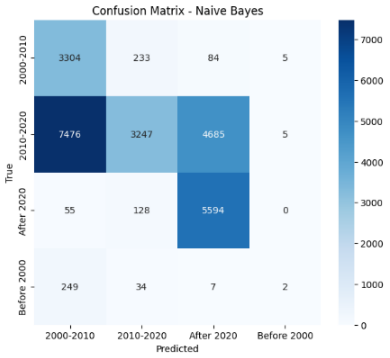
KNN (Price) Naive Bayes (Price) Random Forest (Price)



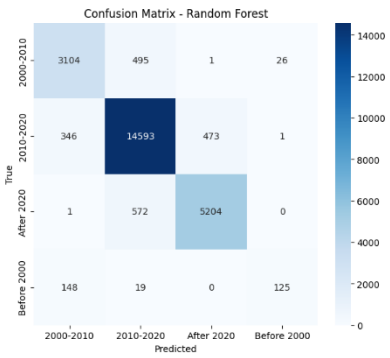
KNN (Mileage) Naive Bayes (Mileage) Random Forest (Mileage)



KNN (Year)



Naive Bayes (Year)



Random Forest(Year)

Statistical Significance Analysis

After running all classification experiments, this section checks whether the performance difference between the two best models is statistically significant. Here the goal is to see if the top 2 models (based on F1-macro score) are truly different in performance, or if their performance differences are just due to random chance in cross-validation folds.

Statistic Scores for Price Category:

• T-test for Accuracy: t-statistic = 16.005

• T-test for F1-macro: t-statistic = 2.112

• T-test for F1-micro: t-statistic = 16.005

• T-test for AUC: t-statistic = 2.055

Statistic Scores for Mileage Category:

• T-test for Accuracy: t-statistic = 6.127

• T-test for F1-macro: t-statistic = 5.371

• T-test for F1-micro: t-statistic = 6.127

• T-test for AUC: t-statistic = 7.979

Statistic Scores for Year Category:

• T-test for Accuracy: t-statistic = 2.876

• T-test for F1-macro: t-statistic = 0.747

• T-test for F1-micro: t-statistic = 2.876

• T-test for AUC: t-statistic = 2.527

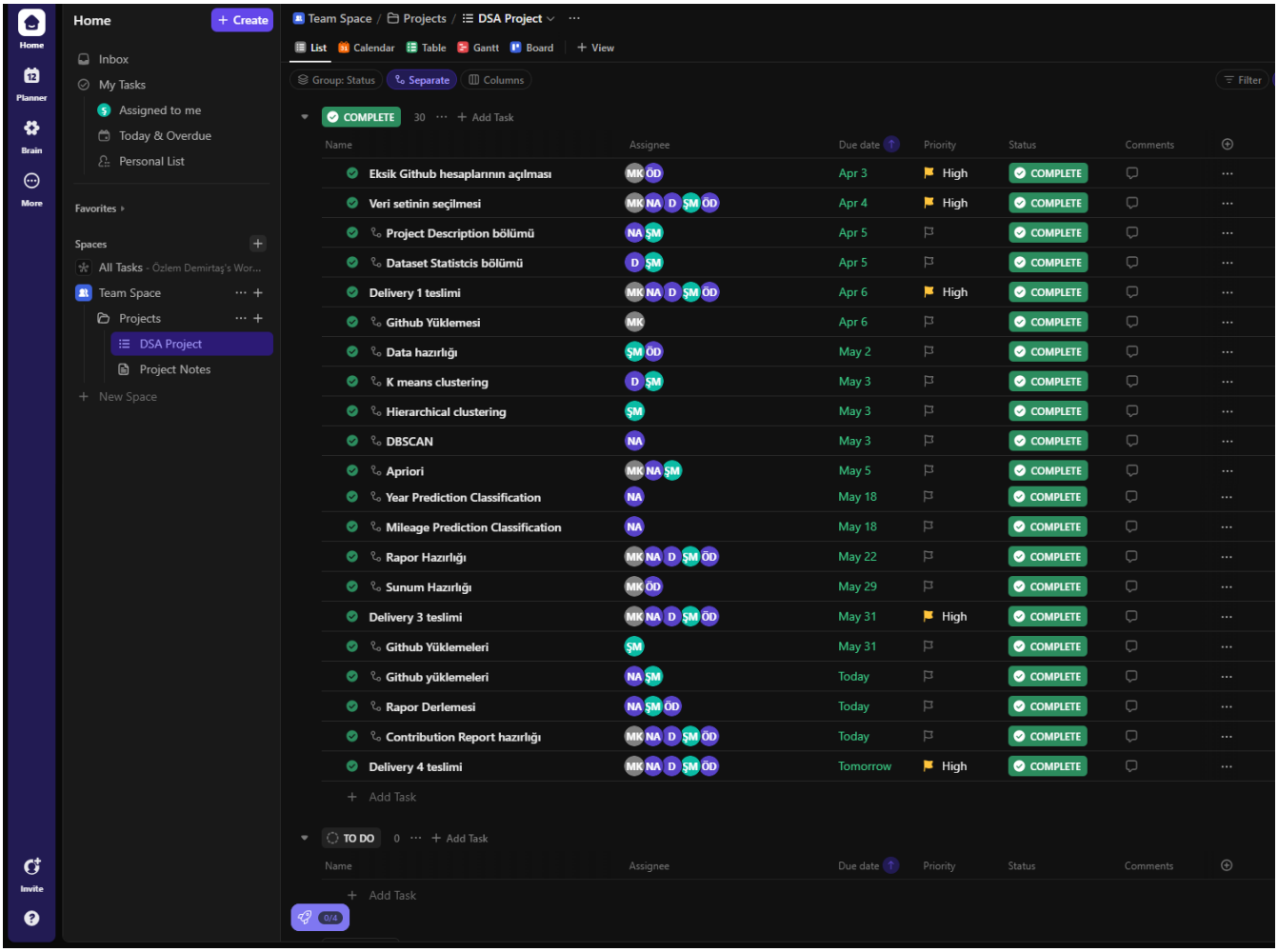
Conclusion and Results

This project explored both descriptive and predictive analytics on a used car dataset. The descriptive phase involved clustering (DBSCAN, K-Means, Hierarchical) and association rule mining (Apriori) to uncover hidden patterns. DBSCAN identified key clusters and outliers, with cluster 0 representing typical second-hand cars. K-Means provided alternative groupings, and Hierarchical Clustering visualized natural data relationships. Association rules revealed strong links, such as manual cars with petrol engines, and model-specific patterns (e.g., Volkswagen Golf with petrol).

For predictive analytics, feature selection (Mutual Information, Lasso, Information Gain) highlighted key attributes like engine power, mileage, and fuel consumption. In regression, SVR outperformed ANN, achieving a lower mean absolute error (€5,134.88) and higher R^2 (0.72), with statistically significant results. For classification (binned price, mileage, year), Random Forest consistently outperformed Naive Bayes and k-NN, delivering the highest F1 and AUC scores across categories.

Overall, the combination of robust clustering techniques and carefully selected predictive models demonstrated practical insights into vehicle segmentation, pricing, and classification. Future improvements could focus on feature engineering, external data integration, and advanced ensemble methods.

Appendix



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- https://autoline.info/-/cars/Germany--c1169cntDE