Beginner ML
GDGoC UIN JAKARTA

ICN

Machine Learning Final Project

Laptop Price Prediction

our Team

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Project Overview

Problems:

- Students face a significant challenge in selecting a suitable laptop that fits their needs and budget due to the overwhelming number of options available on the market.
- Comparing technical specifications between different models is often confusing, leading to uncertainty and a lack of confidence in making the best choice.
- The absence of a data-driven tool to predict laptop prices based on their specifications makes the entire decision-making process inefficient and prone to guesswork.

Goals:

- To build a machine learning model that accurately predicts laptop prices based on key specifications such as RAM, storage, screen size, and processor.
- To deliver trustworthy price estimations that empower students to easily select the right laptop that aligns with their specific needs and budget.
- To attain a robust model performance with an R-squared (R^2) score of approximately 85% by implementing and evaluating algorithms such as Linear Regression, Decision Tree, and Random Forest.

Key Components

Strategy to Reach our Goals

Describing Data

- Understanding the dataset's structure (columns, data types, data noise).
- Identifying initial relationships between features and price.
- Ensuring all essential laptop specification information is available for analysis.

Exploratory Data Analysis

- Visualizing data to understand distributions, outliers, and feature correlations.
- Handling outliers in the target variable.
- Using correlation analysis to find features relevant to the target.

Feature Engineering

- Creating new, more informative features.
- Encoding categorical features.
- Standardizing numerical features.

Modelling + Evaluation

- Building several models for price prediction.
- Using Cross-Validation to evaluate model performance.
- Measuring accuracy using MSE, RMSE, MAE, & R2 Score metrics.
- Selecting the best model based on combined evaluation scores.

Describing Data

- Data Quality & Noise: The dataset is relatively clean, however, several outliers were identified in the price and feature variables.
- Data Types: The dataset contains a mix of numerical features (e.g., RAM, Weight) and categorical features (e.g., Company, Operating System).
- Data Volume: The dataset consists of 1303 rows (records) and 13 columns (features).
- Target Variable: The target variable for prediction is Price_euros, representing the laptop's price in Euros.

	laptop_ID	Company	Product	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price_euros
0	1	Apple	MacBook Pro	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 2.3GHz	8GB	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37kg	1339.69
1	2	Apple	Macbook Air	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8GB	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34kg	898.94
2	3	HP	250 G6	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	8GB	256GB SSD	Intel HD Graphics 620	No OS	1.86kg	575.00
3	4	Apple	MacBook Pro	Ultrabook	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.7GHz	16GB	512GB SSD	AMD Radeon Pro 455	macOS	1.83kg	2537.45
4	5	Apple	MacBook Pro	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 3.1GHz	8GB	256GB SSD	Intel Iris Plus Graphics 650	macOS	1.37kg	1803.60

```
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   laptop_ID         1303 non-null   int64
 1   Company           1303 non-null   object
 2   Product           1303 non-null   object
 3   TypeName          1303 non-null   object
 4   Inches            1303 non-null   float64
 5   ScreenResolution  1303 non-null   object
 6   Cpu               1303 non-null   object
 7   Ram               1303 non-null   object
 8   Memory            1303 non-null   object
 9   Gpu               1303 non-null   object
 10  OpSys             1303 non-null   object
 11  Weight            1303 non-null   object
 12  Price_euros       1303 non-null   float64
dtypes: float64(2), int64(1), object(10)
```

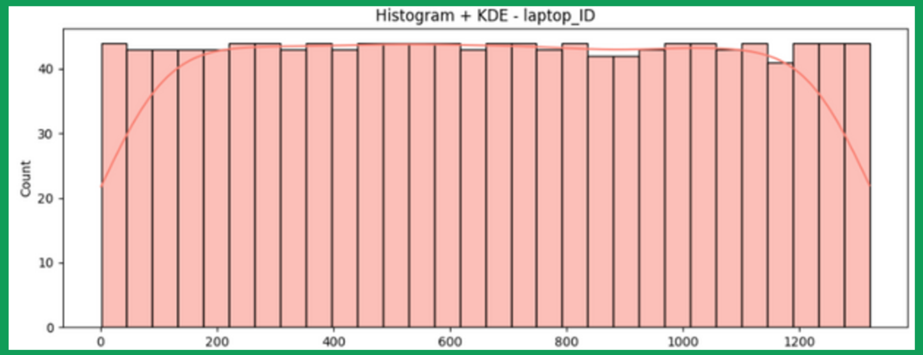
```
Jumlah nilai kosong per kolom:
laptop_ID           0
Company             0
Product             0
TypeName            0
Inches              0
ScreenResolution    0
Cpu                 0
Ram                 0
Memory              0
Gpu                 0
OpSys               0
Weight              0
Price_euros         0
dtype: int64

Jumlah data duplikat: 0
```

```
Jumlah data: (1303, 13)
```

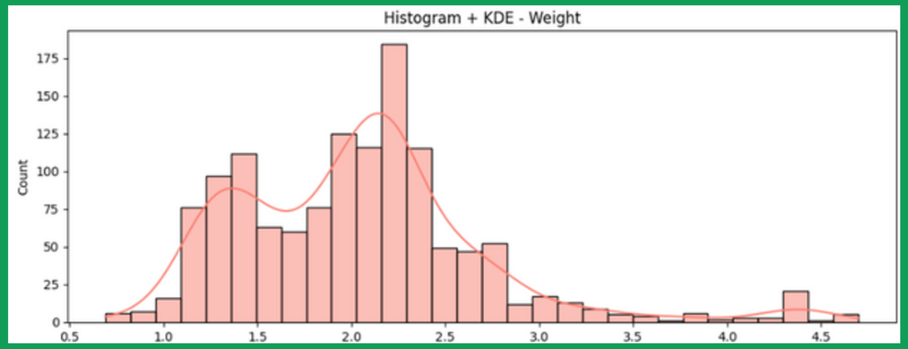
EDA

Univariate - numeric feature

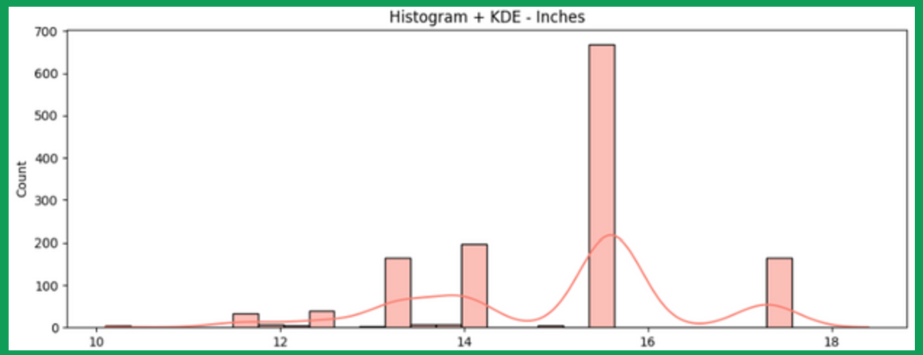
A clear correlation was found between a laptop's price and its specifications, where premium features like larger screens, increased RAM, lighter weight, and high-capacity SSDs consistently lead to a higher cost.



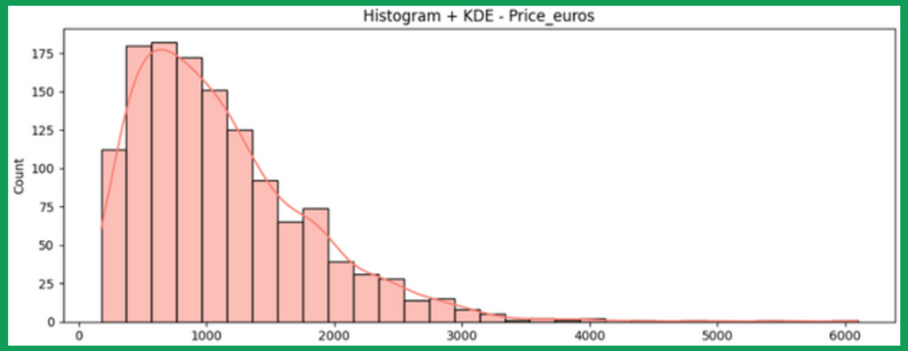
Laptop_ID



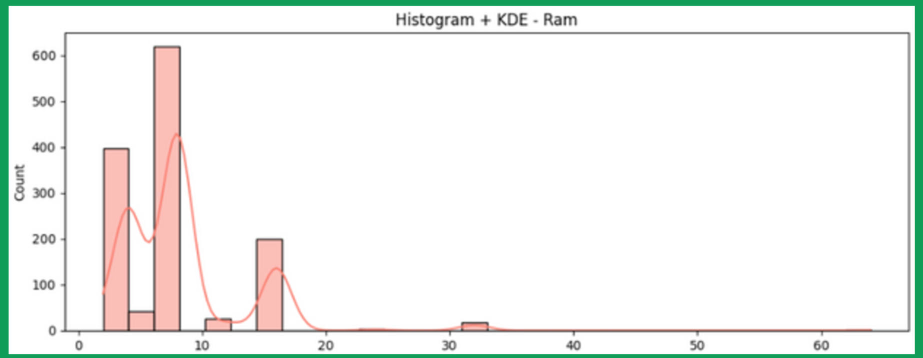
Weight



Inches



Price in euro



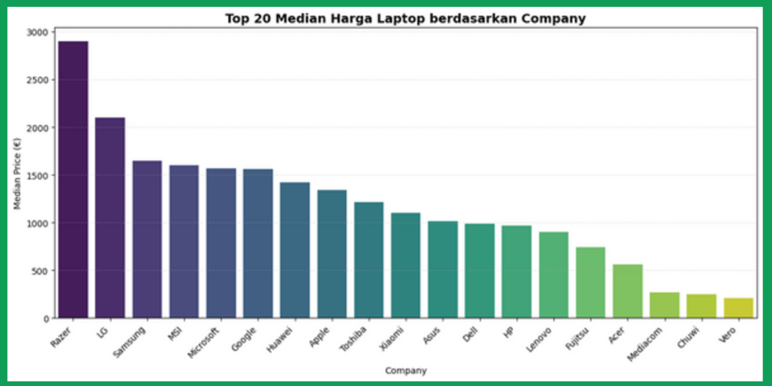
RAM

*median value

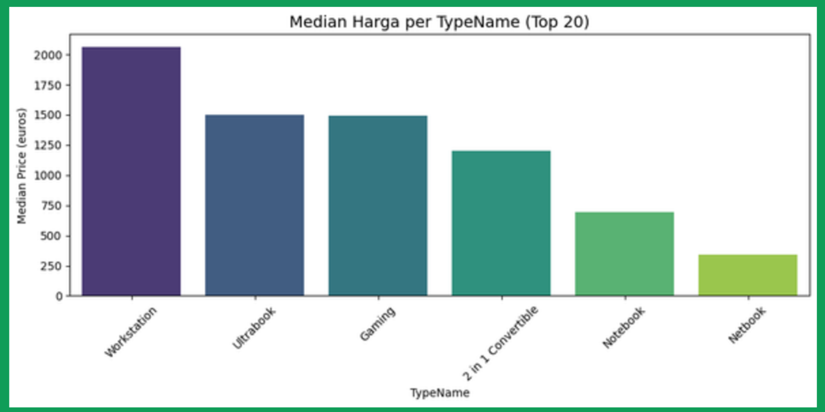
EDA

Univariate - categorical feature

- Premium Components Drive Higher Prices: Laptop prices are heavily influenced by their type (e.g., Workstation/Gaming), premium components like Nvidia Quadro/RTX GPUs, hybrid SSD+HDD storage, and high-quality 4K/IPS displays.
- Brands Define Market Segments: Company branding clearly dictates market position; for instance, Razer targets the premium segment, while Vero and Chuwi focus on the budget market.
- Operating System as a Price Differentiator: macOS consistently positions devices in the upper price range, whereas Chrome OS is a key feature of more affordable laptops.
- Main Market Concentration: The most competitive and active segment of the laptop market is concentrated within the €700–€800 price range.



Company



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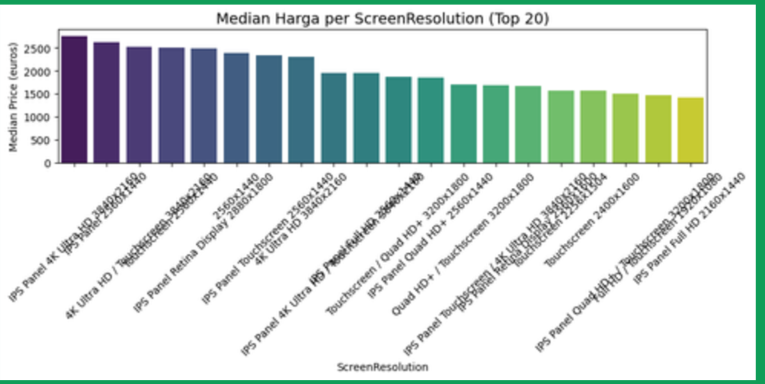
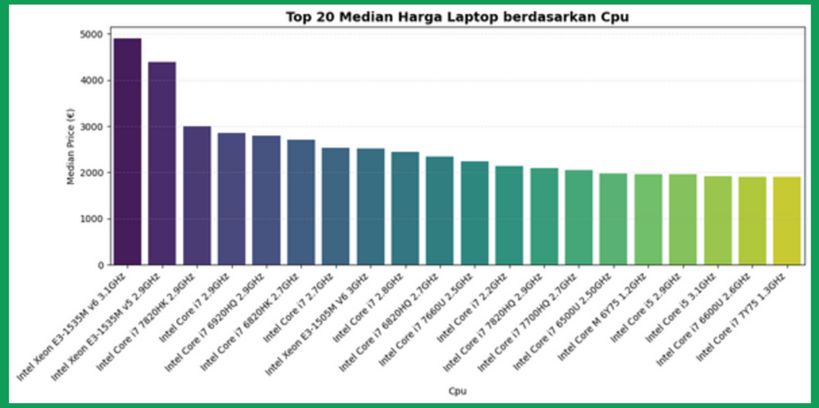
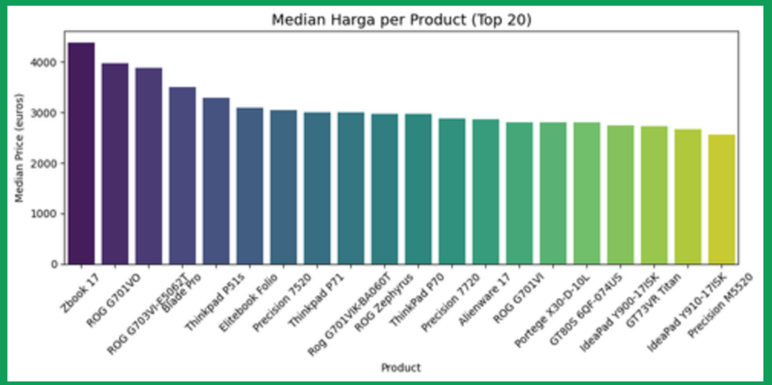


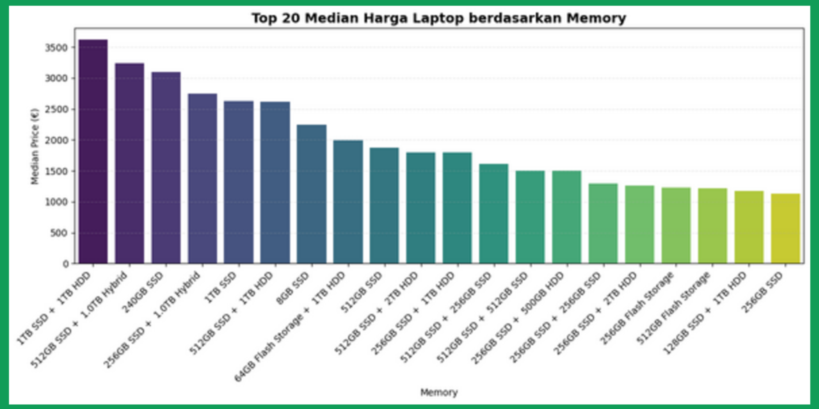
ScreenResolution



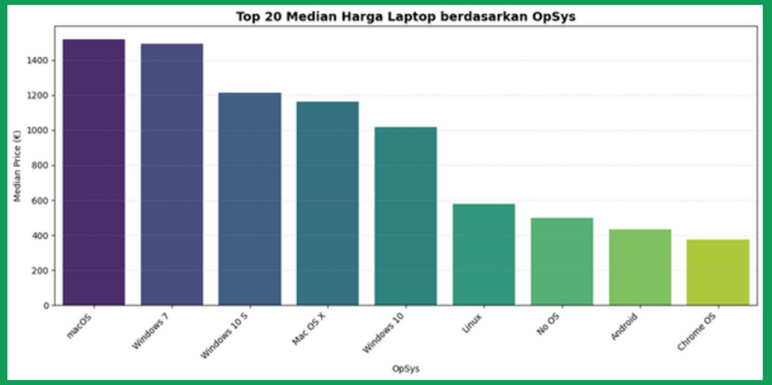
CPU



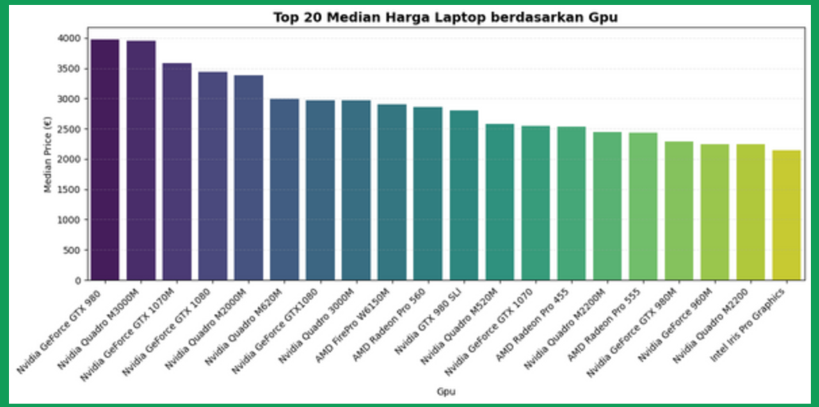
Top Product



Memory



OS

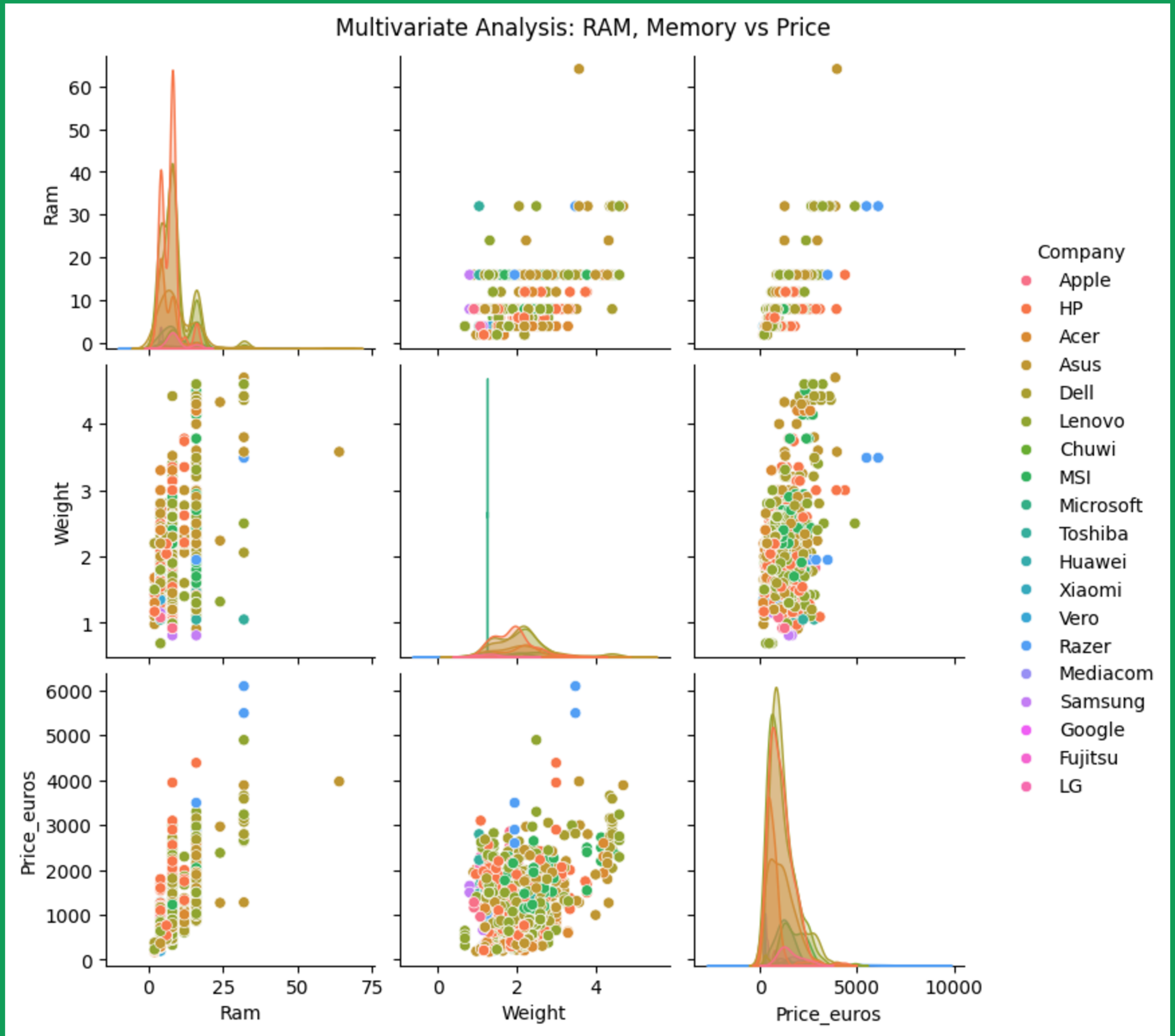


GPU

EDA

Multivariate Analysis

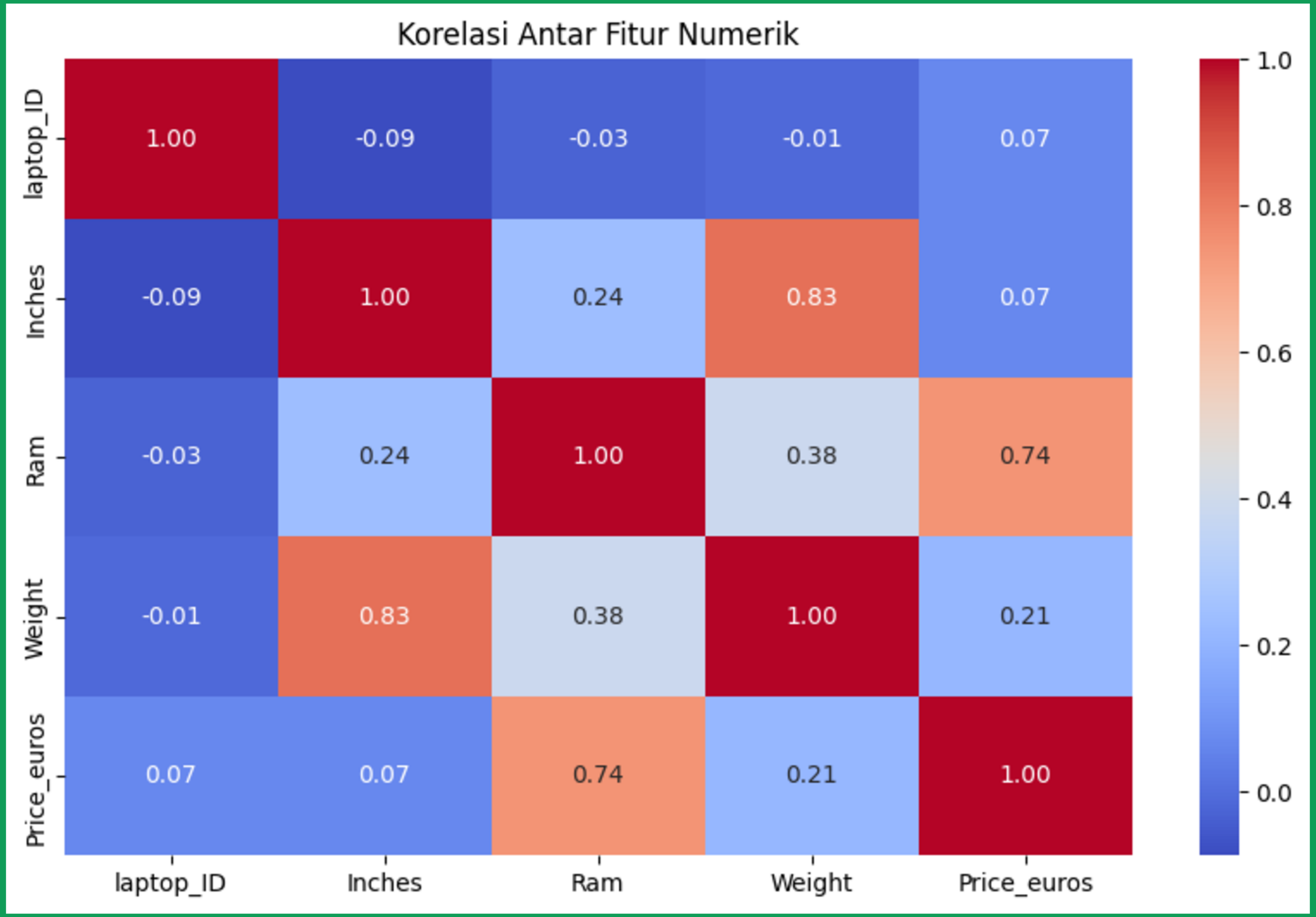
While powerful specifications like ample RAM and storage are key price drivers, brand positioning is a significant factor, enabling premium brands like Apple to command higher prices than competitors with comparable hardware.



EDA

Correlation Features

- A strong positive correlation (0.83) exists between the laptop's screen size and its weight, indicating that larger screens typically mean heavier devices.
- RAM is a significant price driver, showing a strong positive correlation of 0.74 with the laptop's price.
- A moderate positive correlation (0.38) was also observed between the laptop's weight and its RAM capacity.



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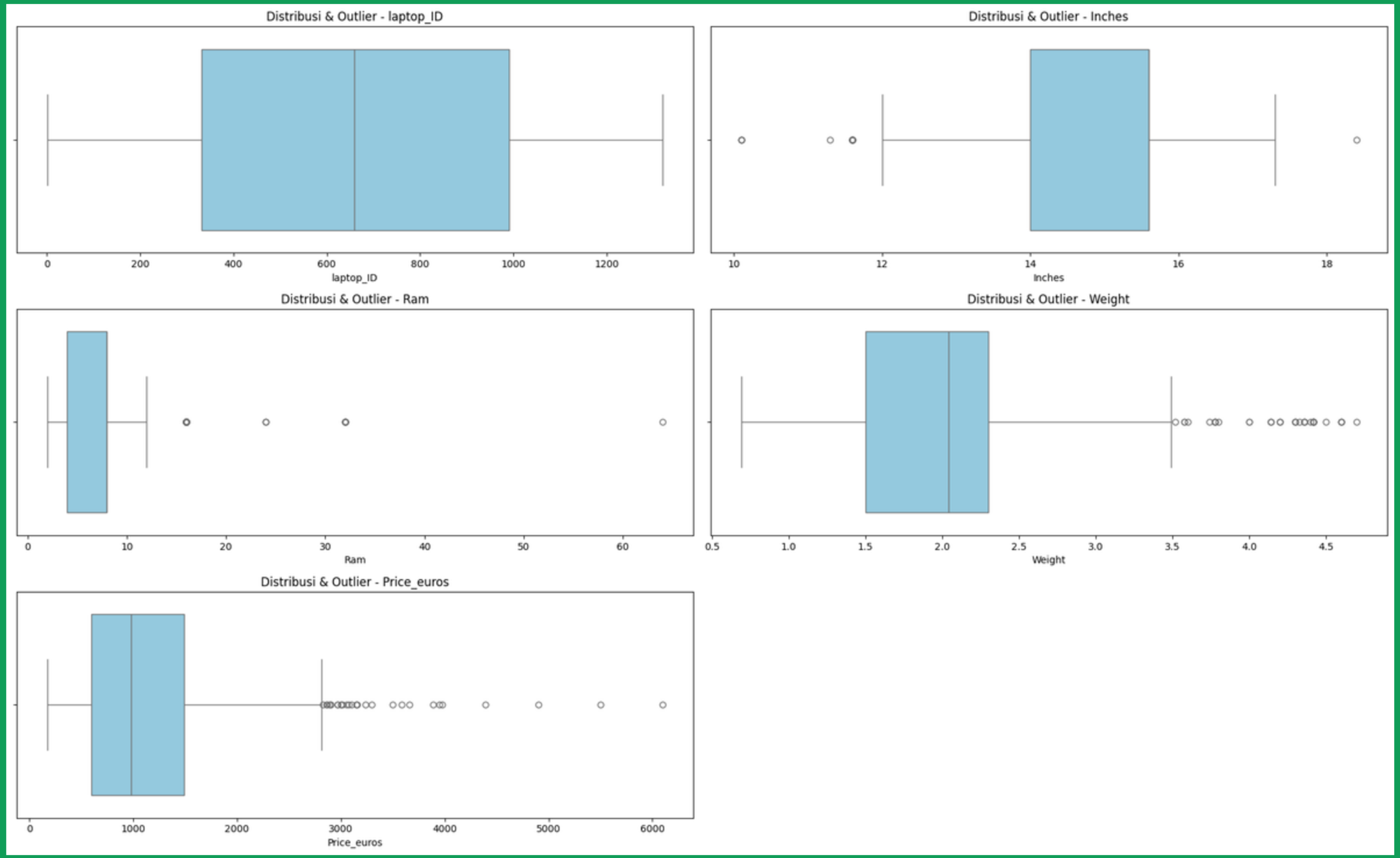
Outlier Check - Numerical Features

- Inches Features (2.99%)
- Ram Features (16.96%)
- Weight Features (3.53%)
- Price_euros Features (2.23%)



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Group 4

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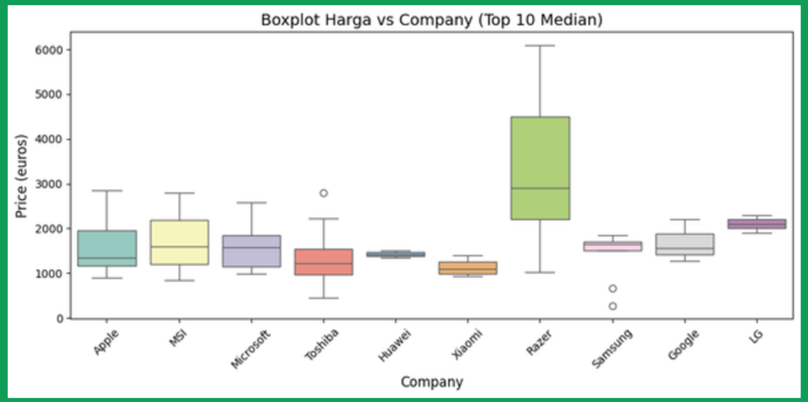
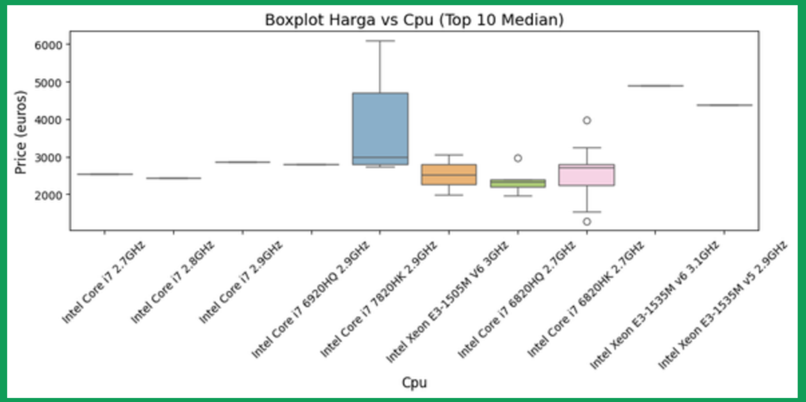
Outlier Check - Categorical Features

- Company features
- Product features
- ScreenResolution features
- CPU features
- Memory features
- GPU features
- OpSys features

*median value



Company



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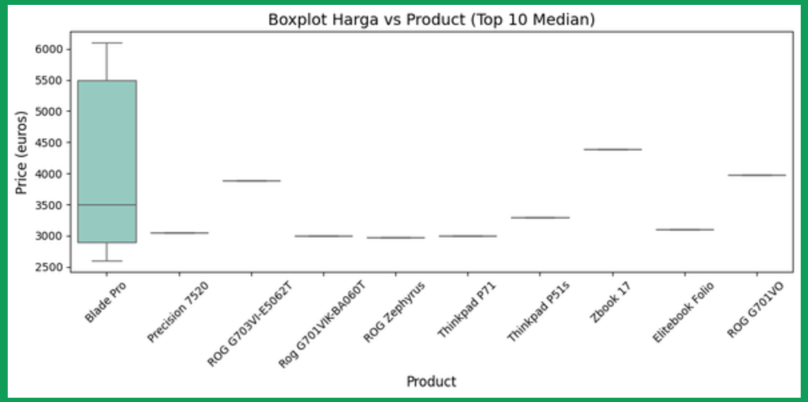
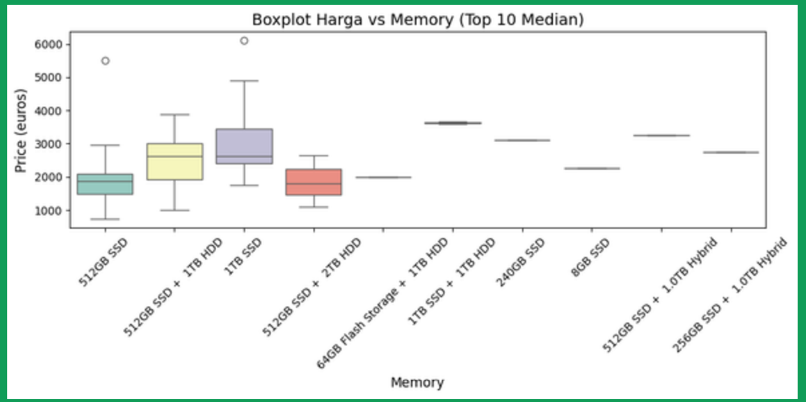
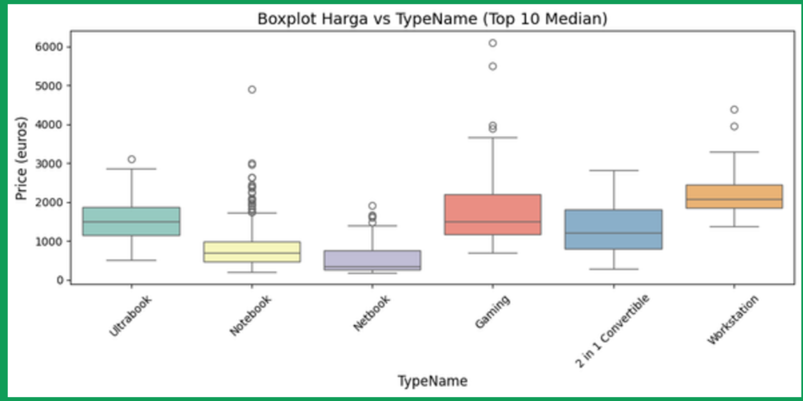


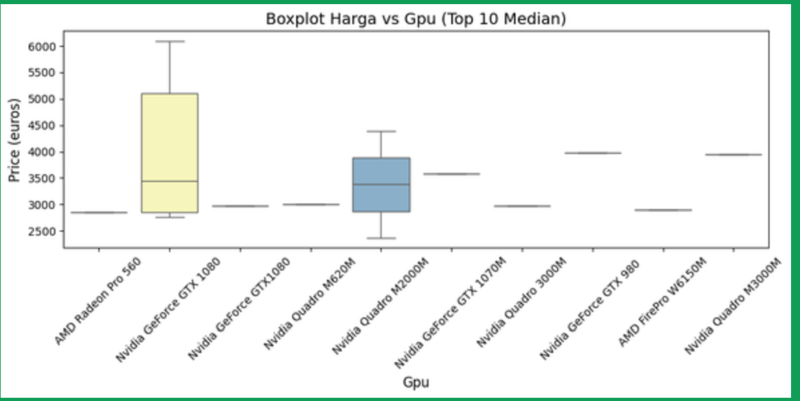
ScreenResolution



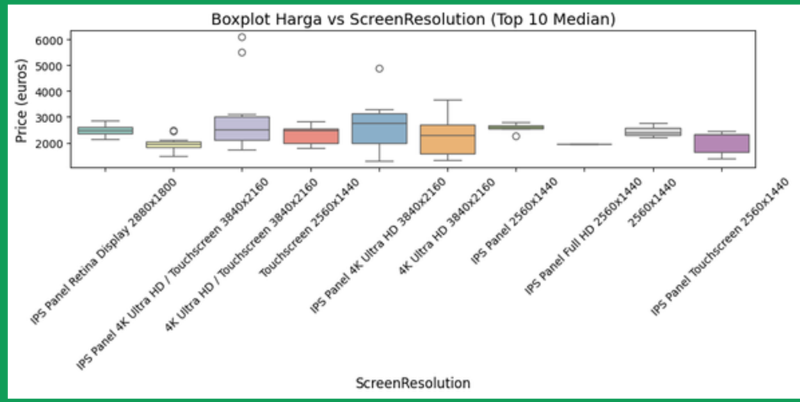
CPU



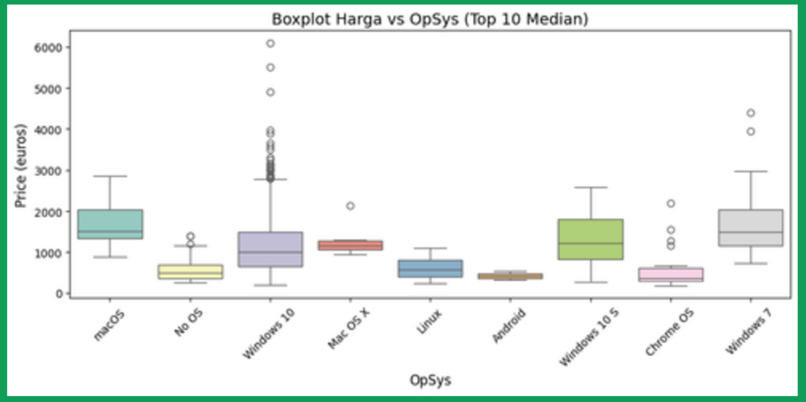
Top Product



Memory



OS



GPU

Feature Engineering

Feature Extraction

GPU_Vendor
CPU_Speed_GHz
Storage_Size
Resolution_Size
Price_Category

Scaling

Features
(StandardScaler)
Target
(MinMaxScaling)

Encoding

One hot encoding
(categorical_features)

Model Building

Challenges - 40%

- The mix of categorical and numerical features complicates the preprocessing stage.
- The presence of outliers in the numerical data could potentially disrupt model accuracy.

Strategy - 30%

- Handling outliers in the target variable using the IQR method.
- Using a Random Forest model, which is robust to outliers in the predictor features.
- Applying One-Hot Encoding for categorical features and StandardScaler for numerical features.

Solution - 30%

- Building and comparing several models: Linear Regression, Decision Tree, and Random Forest.
- Performing Cross-Validation to evaluate model stability and performance.

Model Evaluation

Linear Regression

Training set

Mean Squared Error (MSE)
0.004542147548224353

Root Mean Squared Error (RMSE)
0.06739545643605623

Mean Absolute Error (MAE)
0.05144124566315576

R-squared (R2)
0.9088029221203751

Testing set

Mean Squared Error (MSE)
0.006226653519643523

Root Mean Squared Error (RMSE)
0.07890914724950158

Mean Absolute Error (MAE)
0.061491443767882695

R-squared (R2)
0.8860064481893432

Model Evaluation

Decision Tree

Training set

Mean Squared Error (MSE)
0.0001270762912712981

Root Mean Squared Error (RMSE)
0.011272812039207346

Mean Absolute Error (MAE)
0.0026315968553114024

R-squared (R2)
0.9974485667168049

Testing set

Mean Squared Error (MSE)
0.007464913308670685

Root Mean Squared Error (RMSE)
0.08639972979512543

Mean Absolute Error (MAE)
0.06152064310902882

R-squared (R2)
0.8633371875712251

Model Evaluation

Random Forest

Training set

Mean Squared Error (MSE)
0.0007004405585763358

Root Mean Squared Error (RMSE)
0.026465837575567787

Mean Absolute Error (MAE)
0.018714008439553714

R-squared (R2)
0.9859365792299051

Testing set

Mean Squared Error (MSE)
0.005146084728274344

Root Mean Squared Error (RMSE)
0.0717362162946607

Mean Absolute Error (MAE)
0.05344908861344202

R-squared (R2)
0.9057888038504259

Model Conclusion

The Random Forest model was selected as the final model due to its superior and most stable predictive performance, achieving an R-squared (R^2) score of 0.90. This score indicates that our model can explain 90% of the price variance in laptops based on the selected features. This success was supported by the effective implementation of scaling, encoding, and feature engineering, and was validated using cross-validation to ensure the model does not overfit.

Model Usability

1.For the End-User

The model acts as a smart shopping assistant, providing objective and transparent price estimations. This empowers students to make more confident and well-informed purchasing decisions that align with their budget.

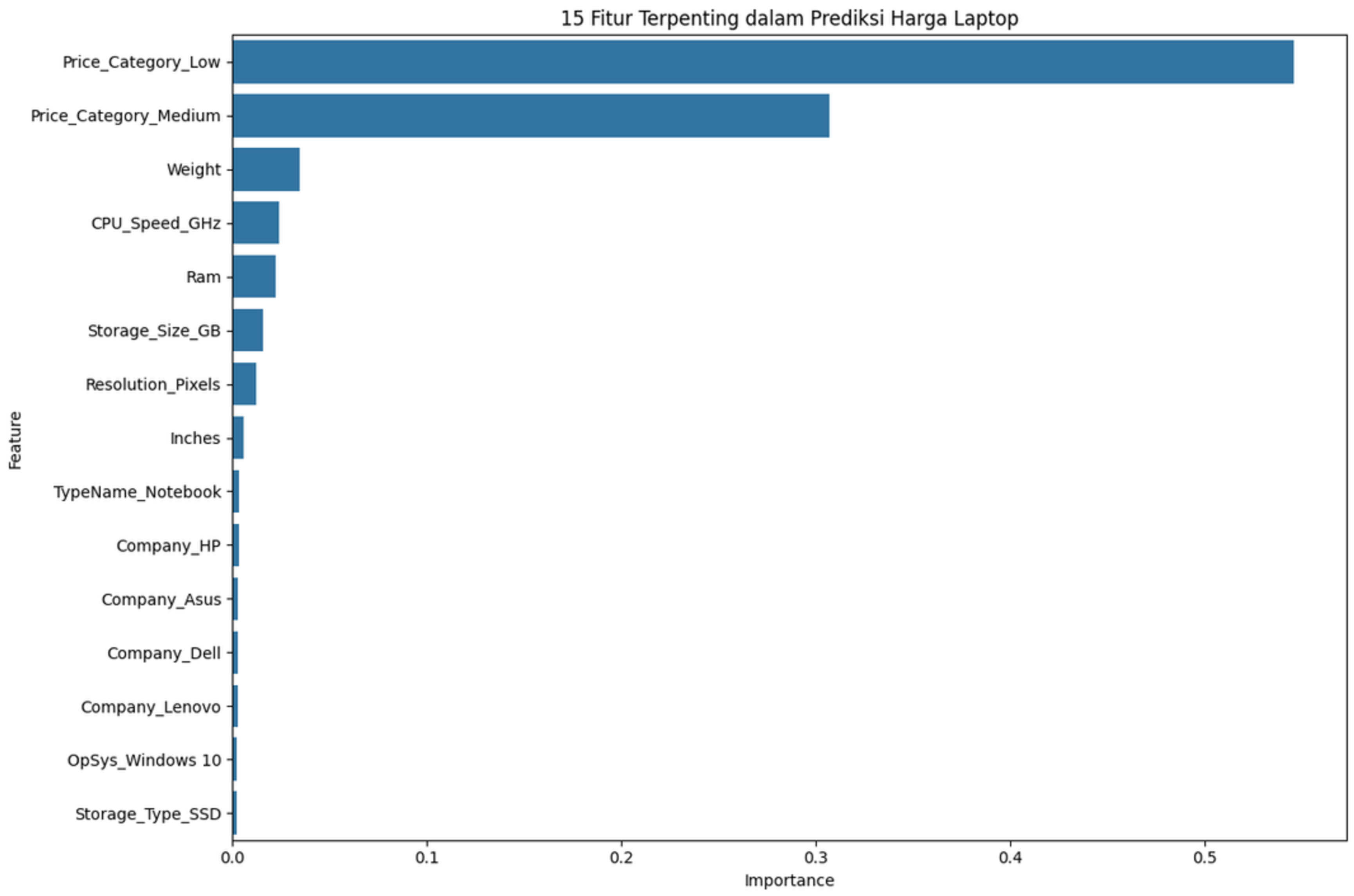
2.Bisnis Usability

This model serves as a foundation for future innovation. It can be integrated into a web application, developed into a public API, or enriched with real-time data to create an even more advanced laptop comparison tool.

3.For Developers

Serves as a business strategy optimization tool. Companies can leverage this model to set competitive pricing, develop sharper product segmentation, and manage inventory more efficiently based on trends in high-demand specifications.

Data Analysis



- Most Impactful Feature Engineering: The engineered feature, Price_Category, emerged as the strongest predictor, proving that market segmentation is a fundamental factor in price determination.
- Core Specifications Remain Dominant: RAM, CPU Speed, and Storage Size consistently form the most influential trio of technical specifications driving the price.
- Consumers Prioritize Specs Over Brand: Interestingly, the influence of the Brand and Operating System was significantly lower than that of hardware specifications, indicating a highly value-oriented market.

Recomendation

1.For the End-User (Students)

Focus your budget on the core specification trio—RAM, CPU, and Storage—to get the best performance for your money.

2.For Producers & Retailers

Use these core specifications as the foundation for your pricing and product segmentation strategies to attract value-oriented consumers.

3.For Developers

Continue to invest in feature engineering, as it has proven to be highly effective in boosting the model's accuracy.

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Thank you

Our model successfully predicts laptop prices with 90% accuracy, empowering students to make smarter purchasing decisions.

Let's Connect:

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