IT-326

Lung Cancer
Data Mining

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PROBLEM STATEMENT & OBJECTIVES

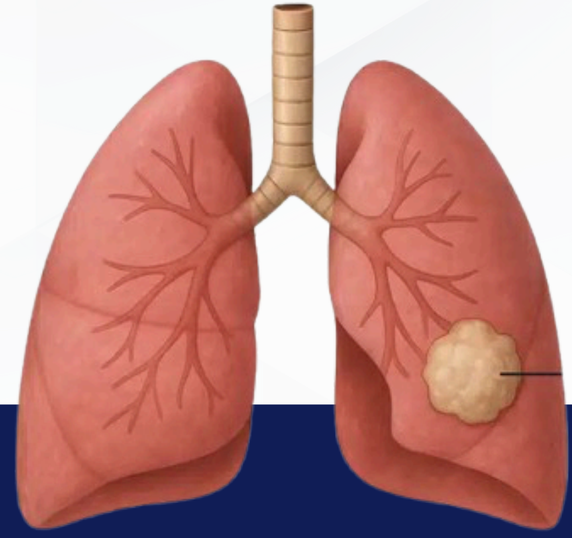
- Dataset of lung cancer patients from Kaggle.
- Includes demographic, lifestyle, exposure, and medical risk factors.
- Objectives
- Understand the relationship between **risk** factors and **lung cancer**.
- **Build** classification models to predict lung cancer.
- Cluster patients into **meaningful** risk groups.

DATASET DESCRIPTION

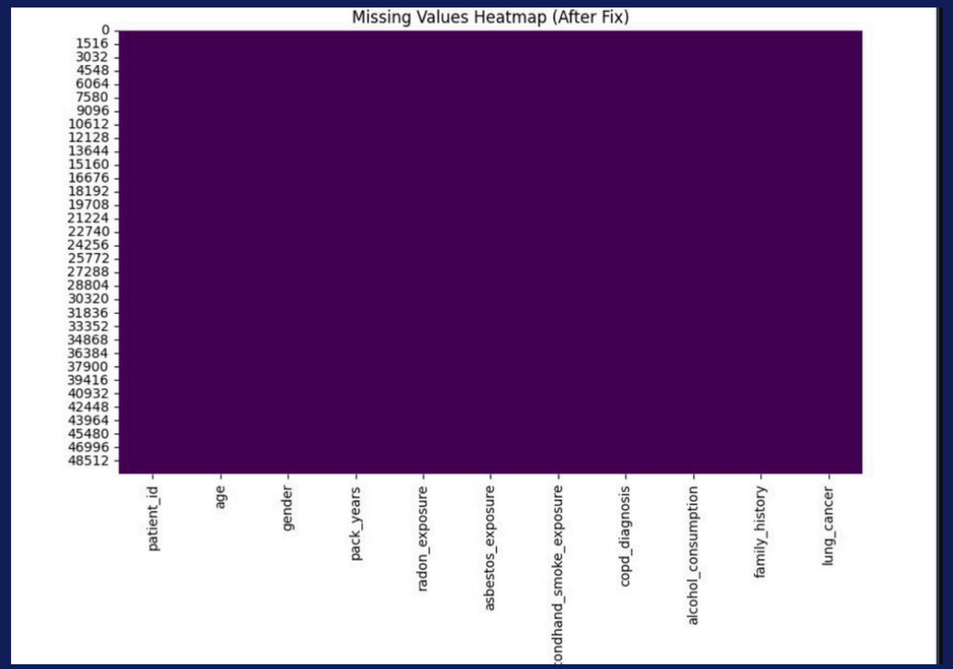
- **50,000** records, **11** attributes
- Target: **lung_cancer** (Yes / No)

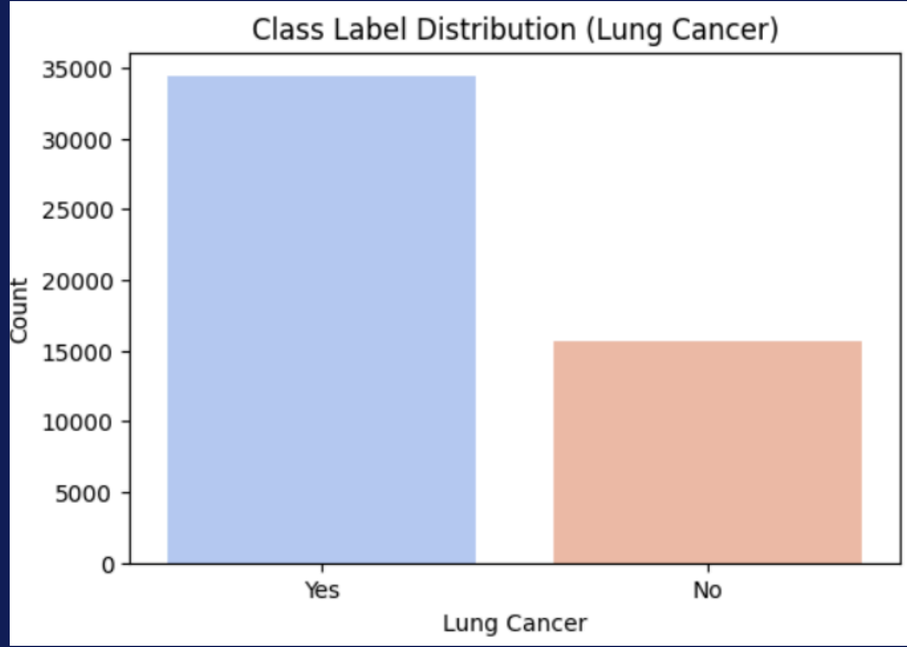
EXAMPLE FEATURES:

- age, gender
- pack_years (smoking history)
- radon_exposure,
- asbestos_exposure
- secondhand_smoke_exposure
- copd_diagnosis,
- alcohol_consumption,
- family_history



EXPLORATORY DATA ANALYSIS (EDA)





- **No missing** values detected across all features.
- Dataset is **imbalanced**: more “Yes” cases than “No”.

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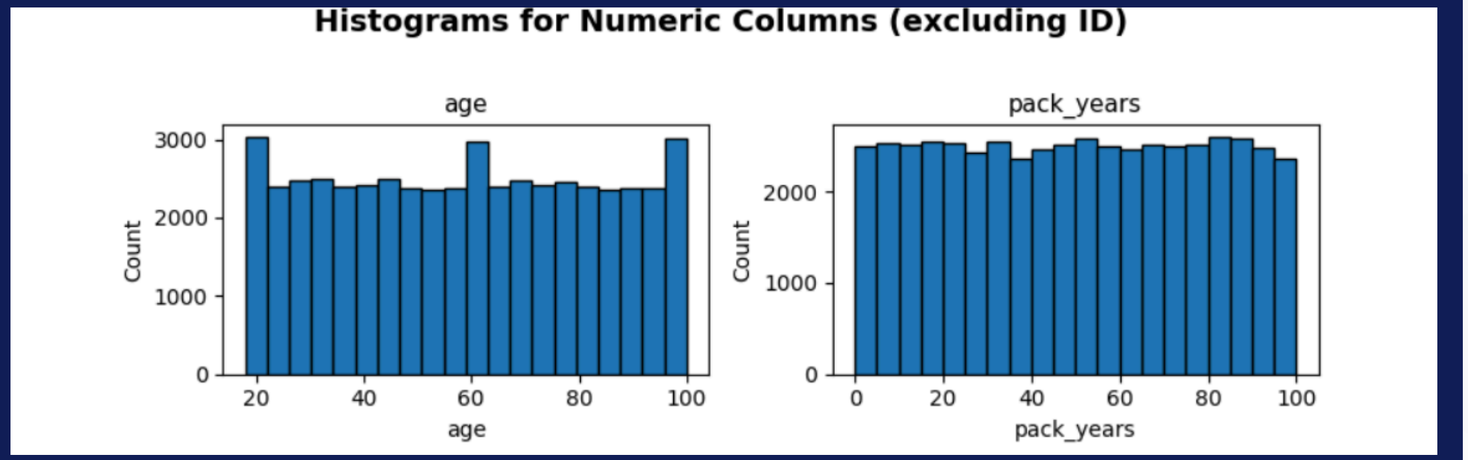
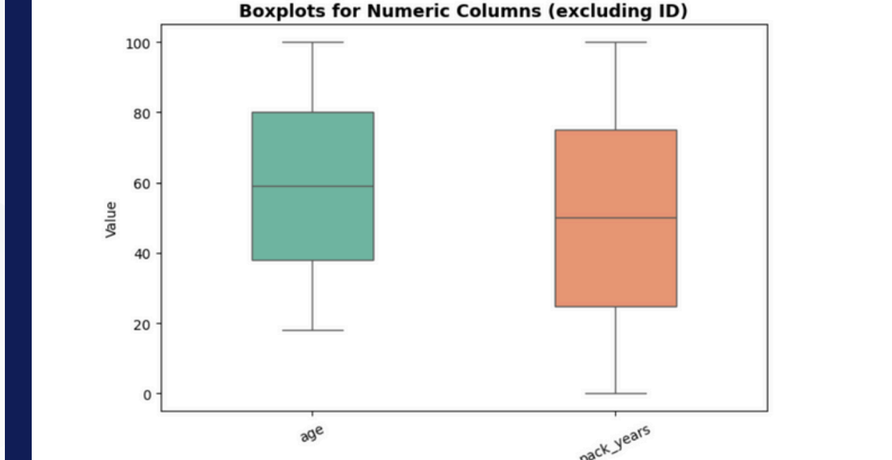
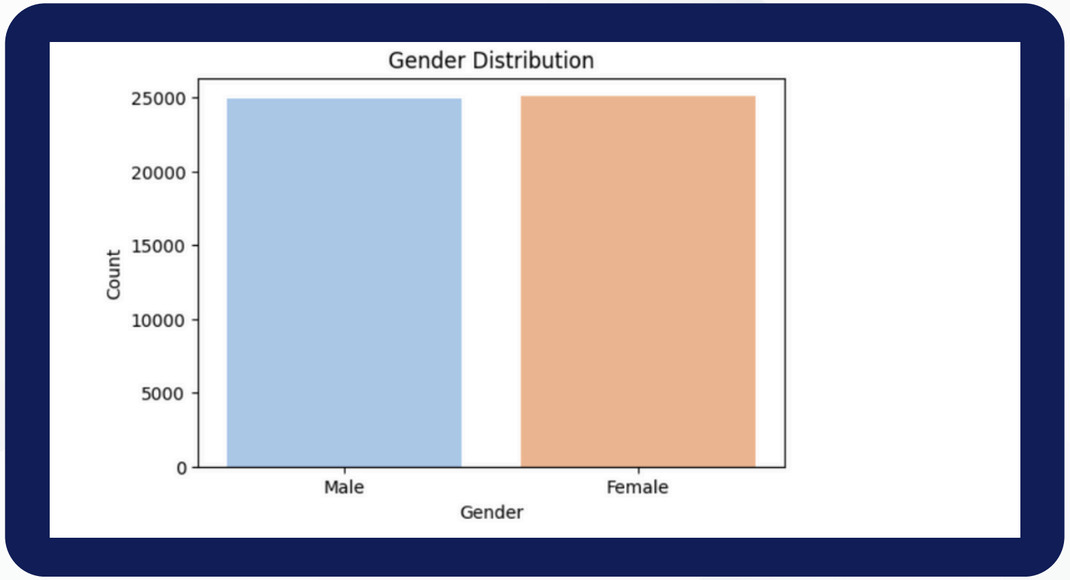
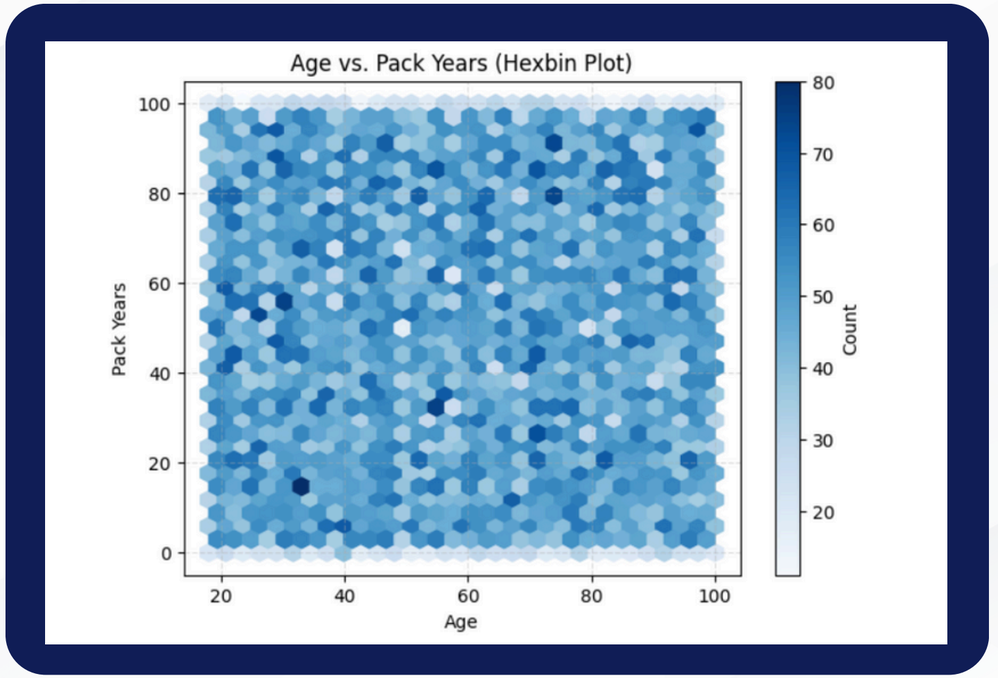




- **Age** and **pack_years** show wide, evenly distributed ranges.
- Both **age** and **pack_years** show normal spread with **no significant outliers**."

EXPLORATORY DATA ANALYSIS (EDA)





- Balanced **gender** distribution (50%–50%).
- **Age** and **pack_years** appear uniformly distributed, with no clear linear relationship. The density pattern indicates no strong correlation between the two variables.

PRE-PROCESSING

Several preprocessing techniques were applied to **clean** and **prepare**

We applied **three** preprocessing techniques:

age
69
32
89
78
38
100

Before

age
Senior
Young
Senior
Senior

After

DISCRETIZATION

lung_canc	family_hist	alcohol_cc	copd_diag	secondhar	asbestos_	radon_exp	pack_year	gender
No	No	Moderate	Yes	No	No	High	66.02524	Male
Yes	Yes	Moderate	Yes	Yes	No	High	12.7808	Female
Yes	No	None	Yes	Yes	Yes	Medium	0.408278	Female
Yes	No	Moderate	No	Yes	No	Low	44.06523	Female

After

	age	gender	family_history	copd_diagnosis	asbestos_exposure	secondhand_smoke_exposure	alcohol_consu
0	2	1	0	1	0	0	
1	0	0	1	1	0	1	
2	2	0	0	1	1	1	
3	2	0	0	0	0	1	
4	0	0	1	1	1	0	

ENCODING

pack_year
66.02524
12.7808
0.408278
44.06523
44.43244
81.18055
18.15675
27.51112

Before

pack_year
0.660248
0.127785
0.004055
0.44064
0.444313
0.811807
0.181546
0.275093

After

NORMALIZATION

CLASSIFICATION

- Classification is **supervised learning** which mean is need a class lapel to classify the objects.

- We trained our model to be able to predict if the patient has lung cancer or not using (**lung_cancer)** class labe

- build our model We used a decision tree algorithm which is a **recursive algorithm** produces a tree with a leaf nodes representing the final decisions.

CLASSIFICATION TECHNIQUES

1-Data splitting

70/30, **80/20**, and **90/10**

2-Decision Tree Training

Gini Index and **Entropy**.

3-Accuracy Evaluation

comparing predicted labels with actual labels

4-Confusion Matrix

visualize correct vs. incorrect predictions

5-Decision Tree Visualization

We visualized the structure of the Decision Tree

DATA SPLITS

- **Training dataset:** for building the decision tree.
- **Testing dataset:** to evaluate the model.

01

90% Training
10% Testing

0.6378
0.6346

02

80% Training
20% Testing

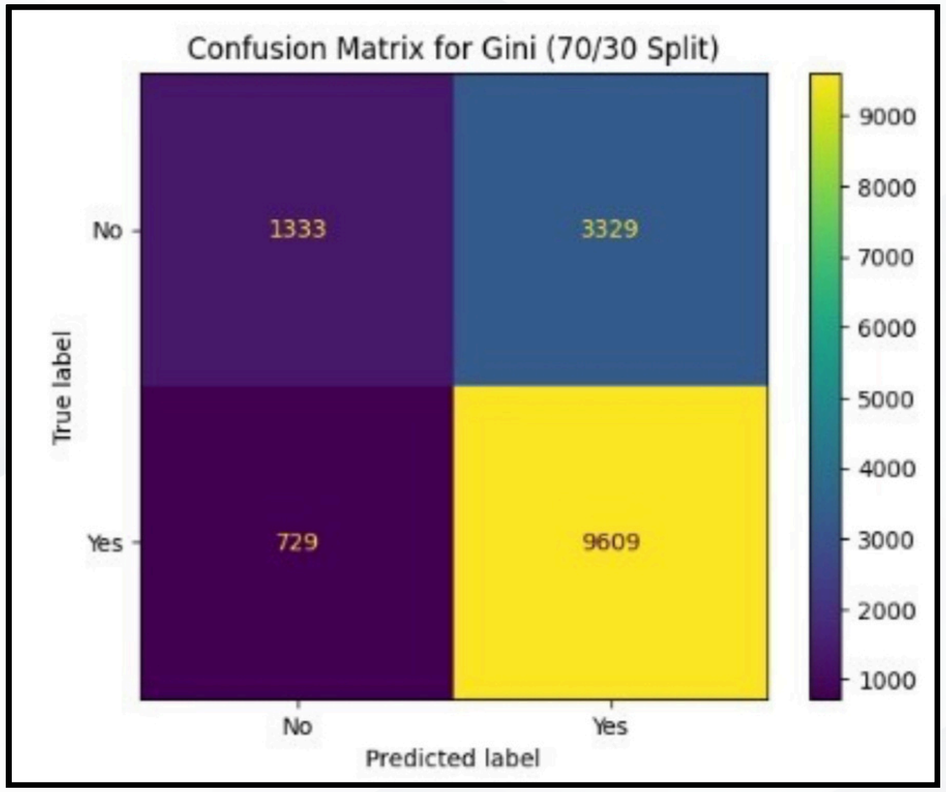
0.6488
0.6487

03

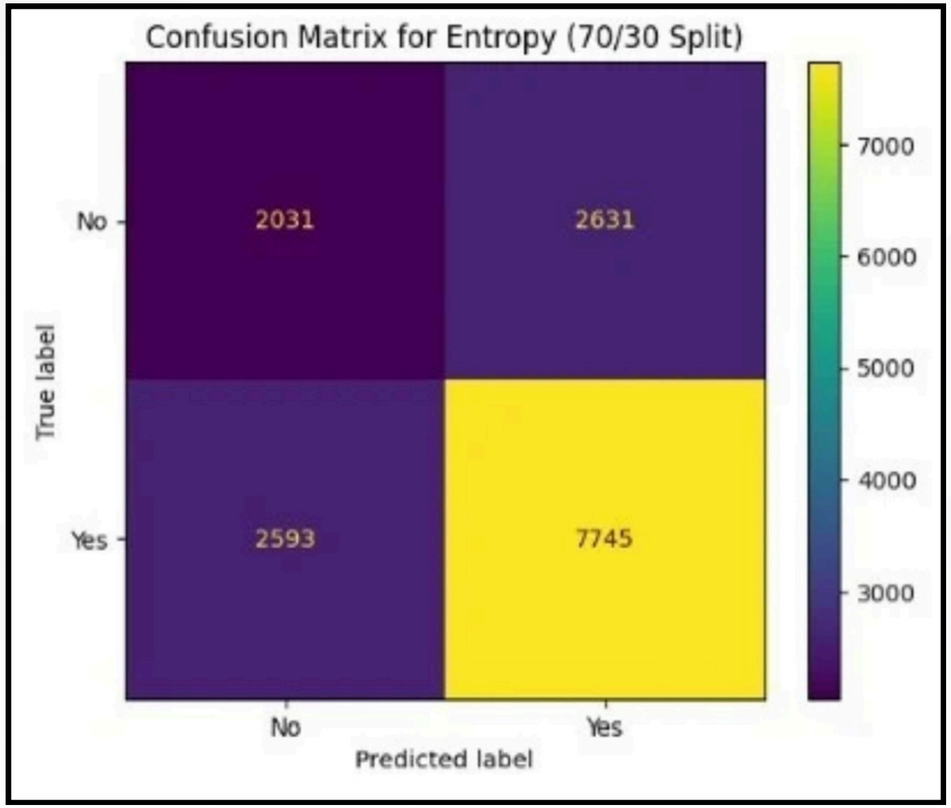
70% Training
30% Testing

0.7294
0.6517

CONFUSION MATRIX



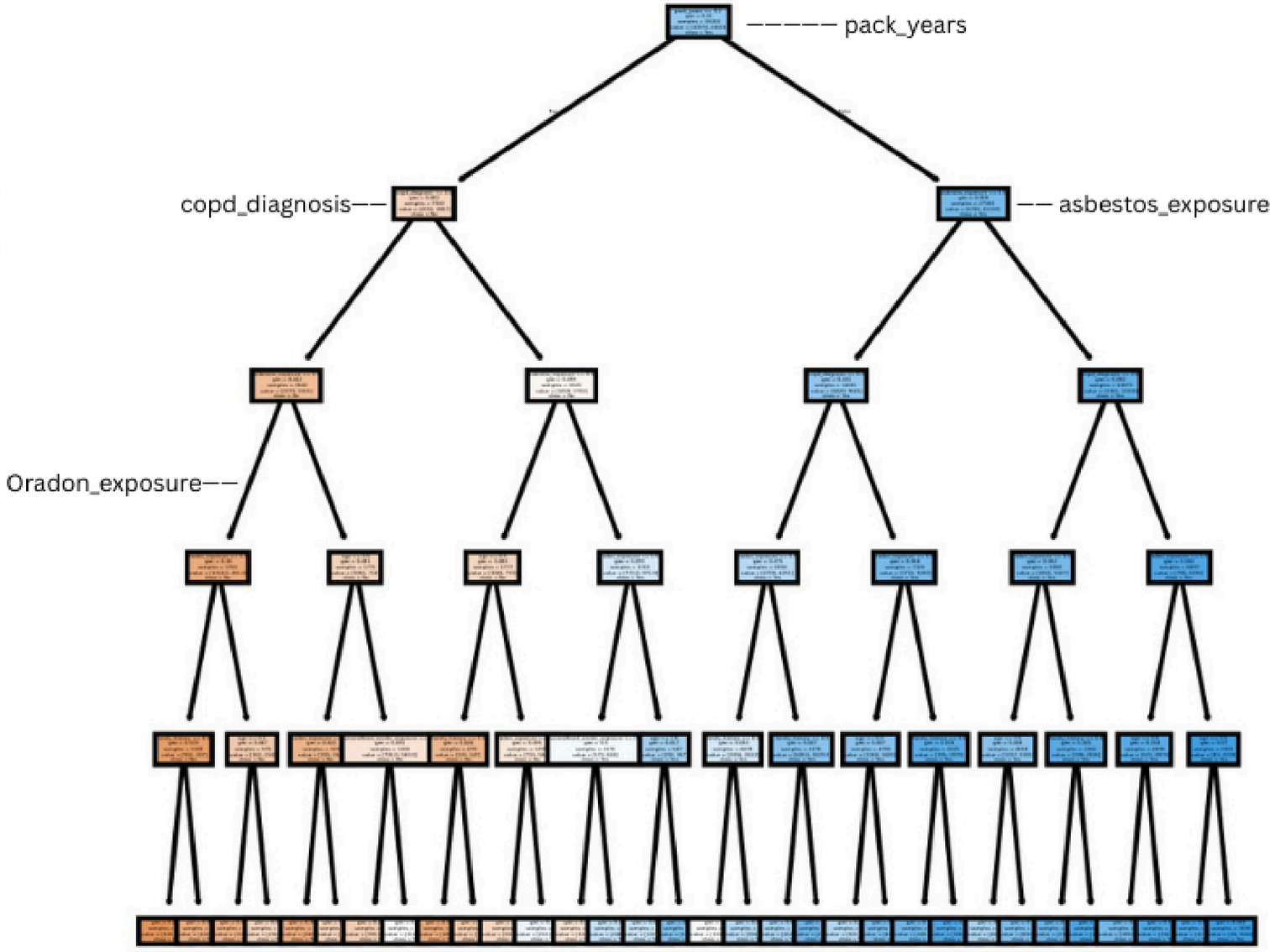
- True Positive (TP): 9609
- False Negative (FN): 729



- True Positive (TP): 7745
- False Negative (FN): 2593

DECIDECISION TREE

Final Decision Tree based on the best-performing model **(Gini, 70/30 split).** This split produced the highest accuracy, and the tree shows the most important features influencing lung cancer prediction.



CLUESTRING

- Clustering is an **unsupervised** learning technique that groups patients based on similarity in their risk-factor attributes.
- the model groups patients who share similar characteristics such as smoking level, radon exposure, asbestos exposure, and other medical risk factors.
- After forming these clusters, the grouping structure can help identify patterns among patients and support future analysis or prediction for new patients with similar risk profiles.

CLUESTRING TECHNIQUES

1-Feature Selection

Remove non-useful columns

2-Standardization

Scale all features to same range

3- K-Means Clustering

Group patients based on similarity

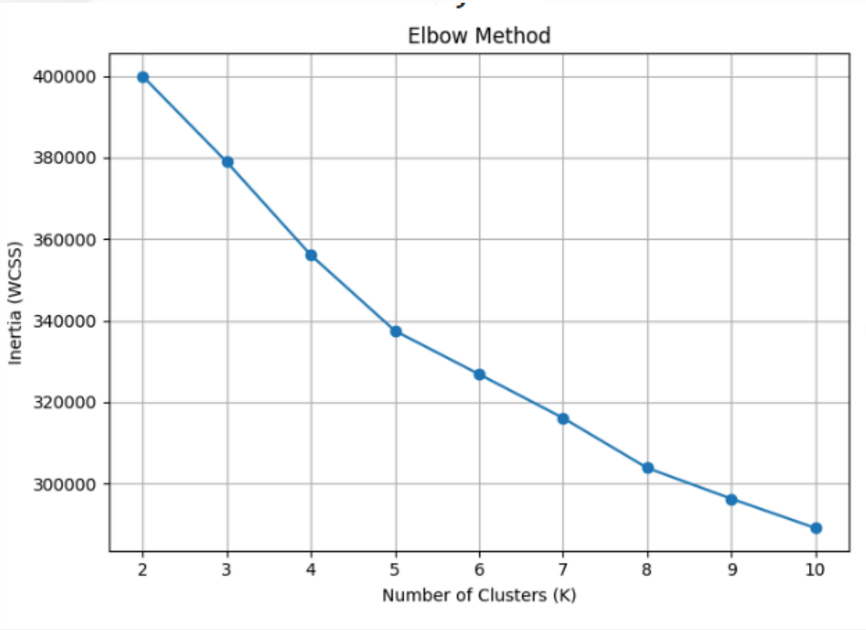
4- PCA Visualization

Reduce dimensions for 3D visualization

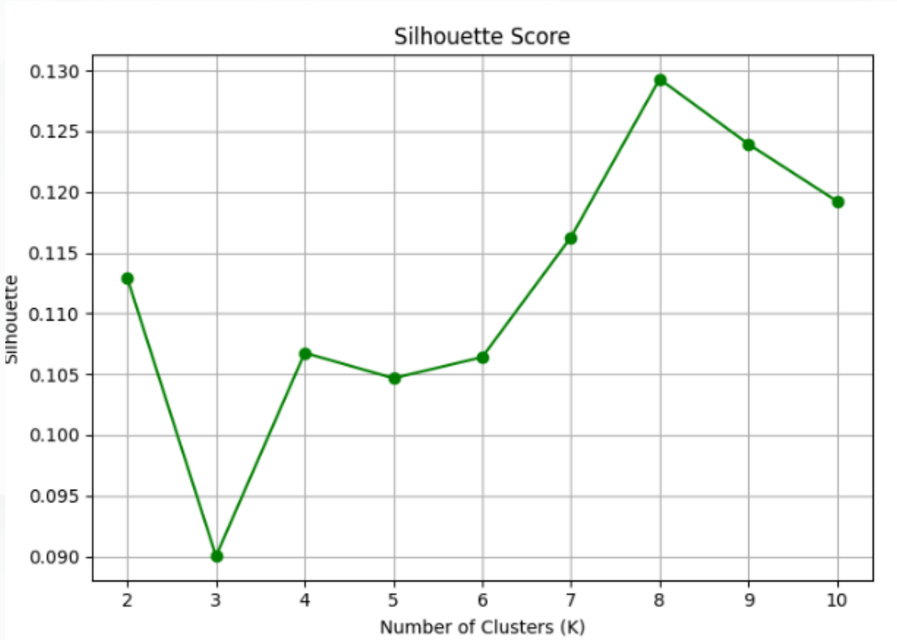
CLUESTRING

Elbow & Silhouette Evaluation

- **Elbow** Method
- No sharp “elbow” point
- **K = 4** and **K = 6** show reasonable stability
- **K = 8** achieves the lowest WCSS → strongest compactness



- **Silhouette** Score
- **K = 8** gives the highest silhouette value
- Indicates the best separation between clusters
- Confirms **K = 8** as the optimal choice
- Conclusion: Both metrics support choosing **K = 8.**



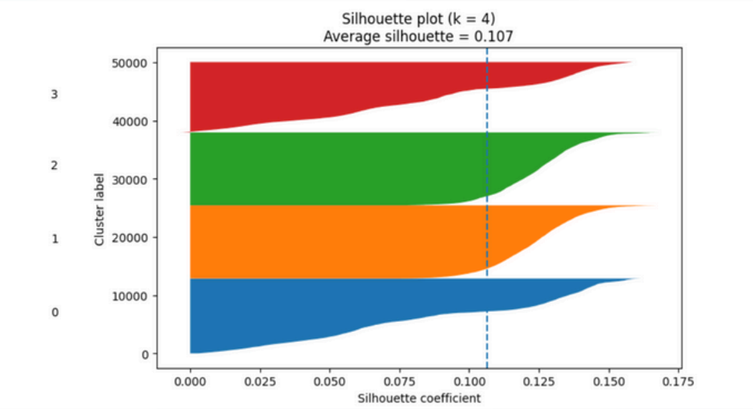
CLUESTRING

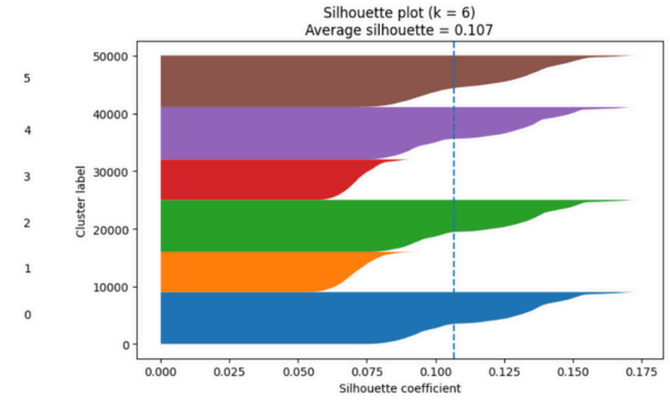
Silhouette Plots for Each K

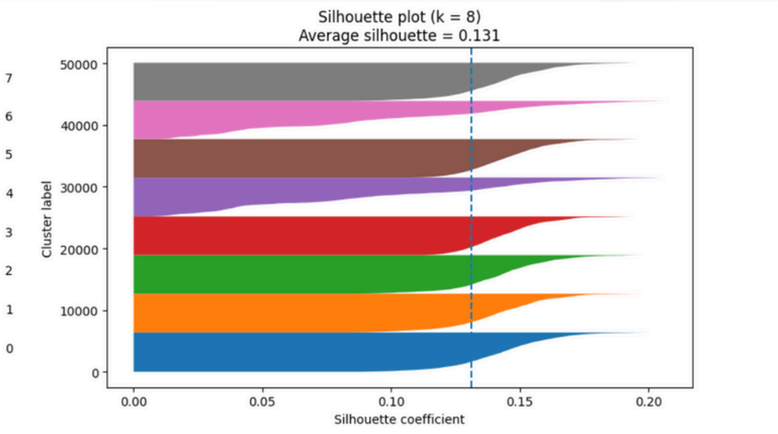
silhouette analysis helps evaluate how well-separated and compact the clusters are.

Below are the silhouette plots for K = 4, K = 6, and K = 8.

- K = 4:Average silhouette ≈ 0.106
- K = 6:Average silhouette ≈ 0.107
- K = 8: Average silhouette ≈ 0.131 (highest, best separation)



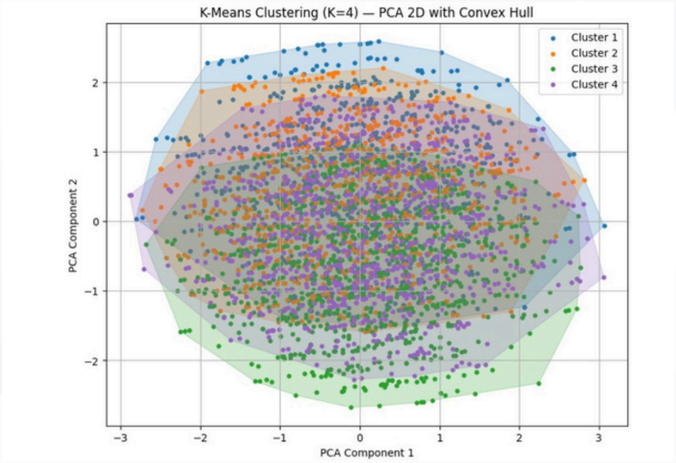




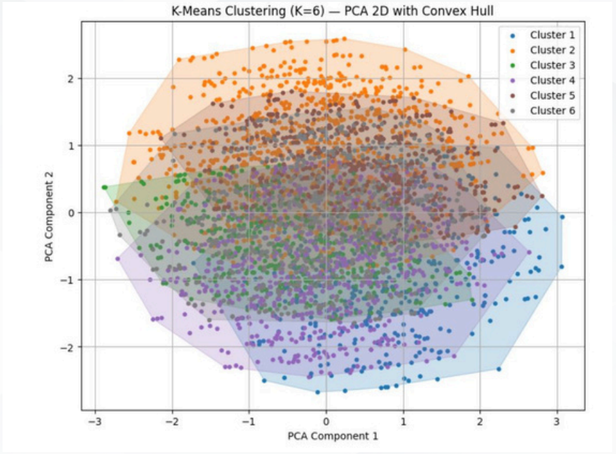
CLUESTRING

PCA CLUSTER VISUALIZATION

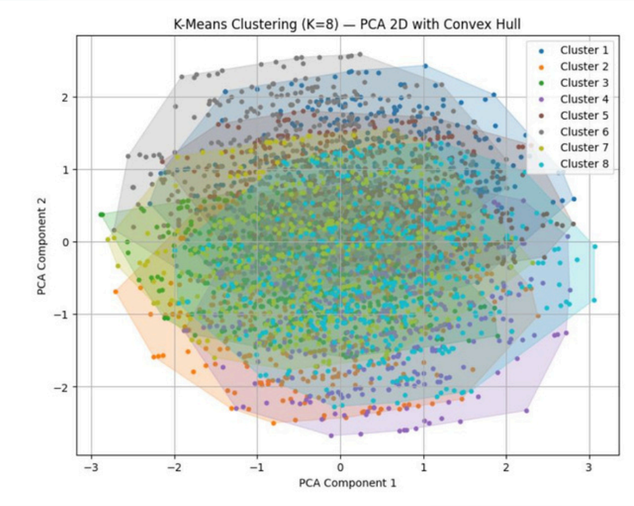
PCA (3D) WAS USED TO VISUALLY COMPARE CLUSTERS FOR K = 4, 6, AND 8.



K = 4
VERY BROAD CLUSTERS
SIGNIFICANT OVERLAP
WEAK SEPARATION



K = 6
SLIGHTLY MORE DEFINED STRUCTURE
OVERLAP STILL PRESENT
MODERATE IMPROVEMENT



K = 8 (MOST CLEAR)
MOST DEFINED CLUSTER BOUNDARIES
BETTER GROUPING AND LOWER OVERLAP
CONVEX HULL VISUALIZATION SHOWS
CLEARER SEGMENTATION

FINAL : K = 8 PROVIDES THE MOST STRUCTURED, COMPACT, AND INTERPRETABLE CLUSTERING.

FINDINGS

- The **70/30 split** gave the highest accuracy across all models.
- Gini outperformed Entropy, achieving the best accuracy (0.729).
- Both models struggled more with predicting the “Yes” class, likely due to feature overlap.
- For clustering, K-means with K=8 produced the best separation (highest silhouette score), **PCA** visualizations confirmed.
- Overall, results show that multiple factors—not a single feature—drive lung cancer risk.
- Most influential features: COPD diagnosis and smoking-related exposures.

RESEARCH PAPER

The research paper used large-scale real-world EHR data, and built a high-dimensional LASSO model achieving strong performance (AUC 0.76).

Our project, in contrast, used a smaller educational dataset and applied a Decision Tree classifier to compare Gini and Entropy criteria, (AUC 0.72).Both works identified smoking and COPD as major predictors of lung cancer While the paper used complex models with external validation, our project demonstrated that Gini with a 70/30 split produced the best and most stable accuracy.Despite differences in scale and methodology, our findings align with the research in highlighting multi-factor influence on lung cancer prediction.

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THANK YOU