Explainable Classification for Non-Small Cell Lung Cancer based on Positron Emission Tomography features and clinical data

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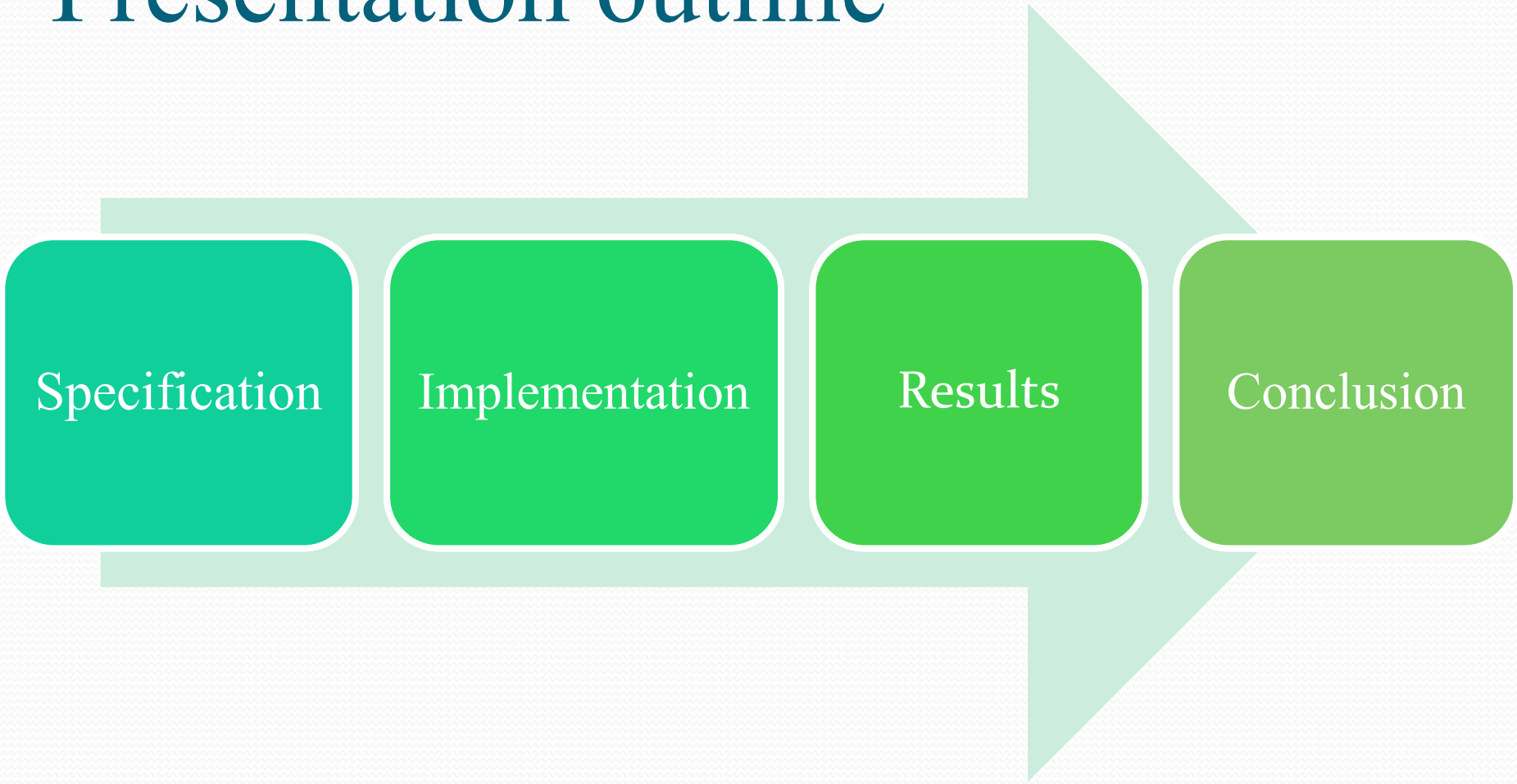
Presentation outline

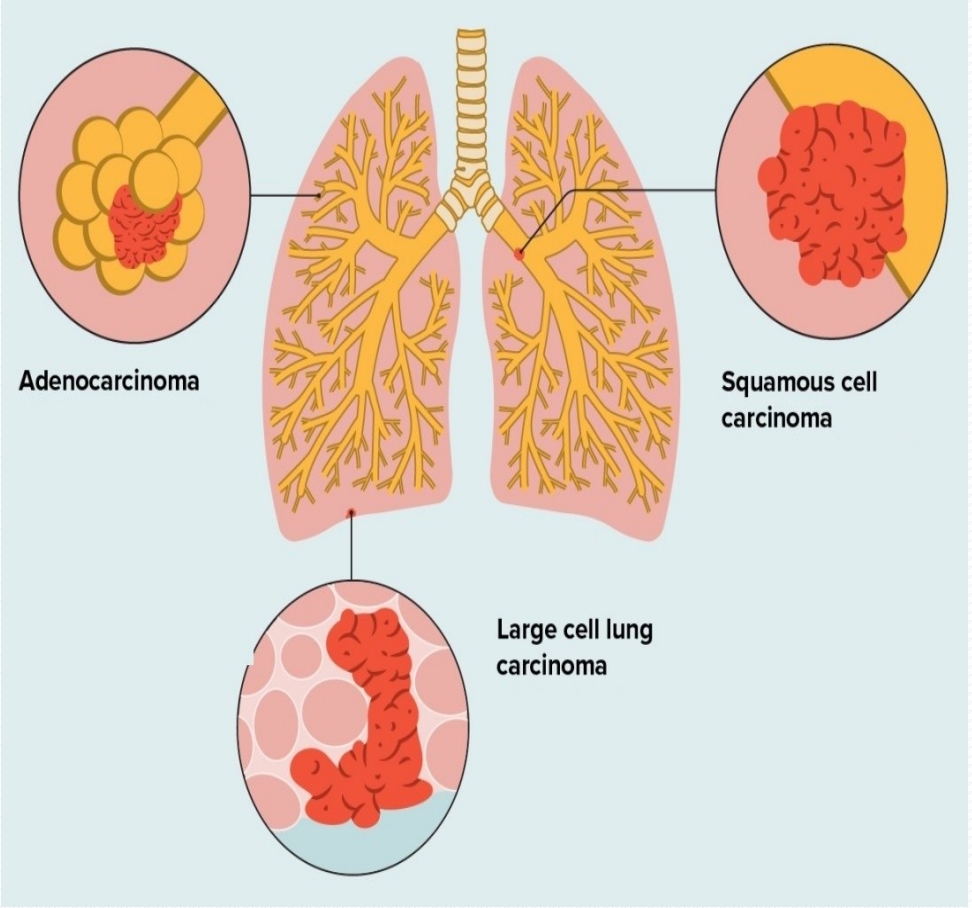


ML In Healthcare

- Customized Medical Decision Support Systems (MDSS)
- Earlier interventions and treatment
- Uses a variety of information (image data from scans, medical history, biometric etc.)
- Still at an early stage – great potential
- Majority of applications are **black-boxes**

NSCLC

- Non-Small Cell Lung Cancer
- Most common form of lung cancer (85% of all lung cancer cases)
- Treatments:
  - Chemotherapy
  - Radiation therapy
  - Targeted therapy
- Types:
  - Adenocarcinoma
  - Large Cell Lung Carcinoma
  - Squamous Cell Carcinoma



Importance of Explainability

- Critical - especially for healthcare applications
- Rules & regulations set explanations as mandatory for automated decision-making systems
- Outlier cases can be reasoned about by human users
- New potential patterns can be pinpointed more effectively

Implementation

Dataset:

- 243 participants
- 54.32% malignant
- 70.37% male
- Ages: 46 to 89 years (67-year old average)
- BMI: 14.36 to 40.88

A/A	Feature Name	Description	Feature Class/Type
1	Gender	Male/female	Demographics
2	Age	Years of age of the patient	Demographics
3	BMI	Body Mass Index	Demographics
4	FDG	F-fluorodeoxyglucose uptake	Medical index
5	SUV	SUV max index	Medical index
6	GLU	Glycemic Load index	Medical index
7	Diameter	Diameter of SPN	Positional Data
8	Position	Position of SPN	Positional Data
9	Limits	Limits of SPN	Positional Data
10	Type	Type	SPNs morphology data
11	Benign/Malignant	Class (as diagnosed by the medical expert)	Reference Variable

Implementation

AI models based on:

- Random Forest
- TabPFN
- LightGBM
- AdaBoost

Performance evaluation:

- Accuracy
- Sensitivity
- ROC curve
- Confusion matrix

Implementation

Methodology Pipeline:

- Hyperparameter Selection (for each model)
- 90/10 train-test split
- 10-Fold Cross Validation
- Selection of best performing model (based on the performance evaluation metrics)
- Explainability layer for selected prediction model

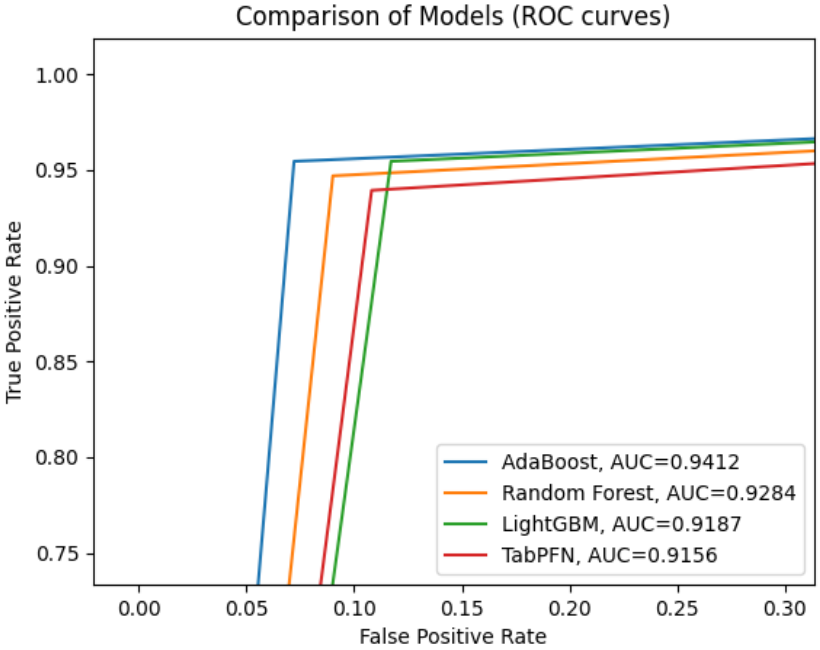
Implementation

Explainability:

- Shapley Additive Explanations (SHAP) analysis
- Summary Plot (depicts weights for all features)
- Decision Diagrams (accurately describes the decision making process of the AI based on feature values)

Comparative Results

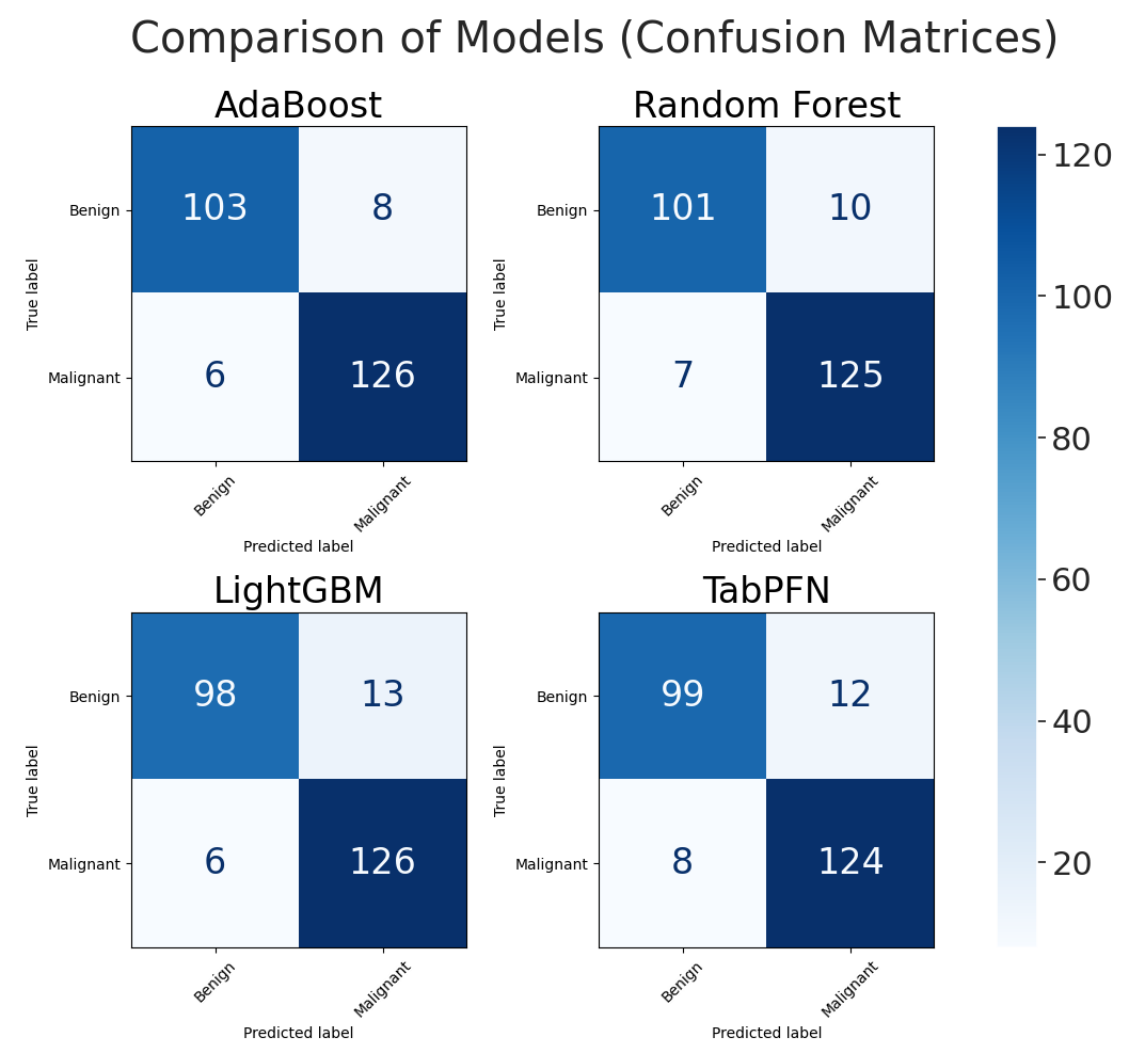
	RF	TabPFN	LightGBM	AdaBoost
Accuracy	93.1%	91.87%	92.67%	94.33%
Specificity	91.21%	89.32%	88.48%	92.96%
Sensitivity	94.95%	94.18%	95.71%	95.71%



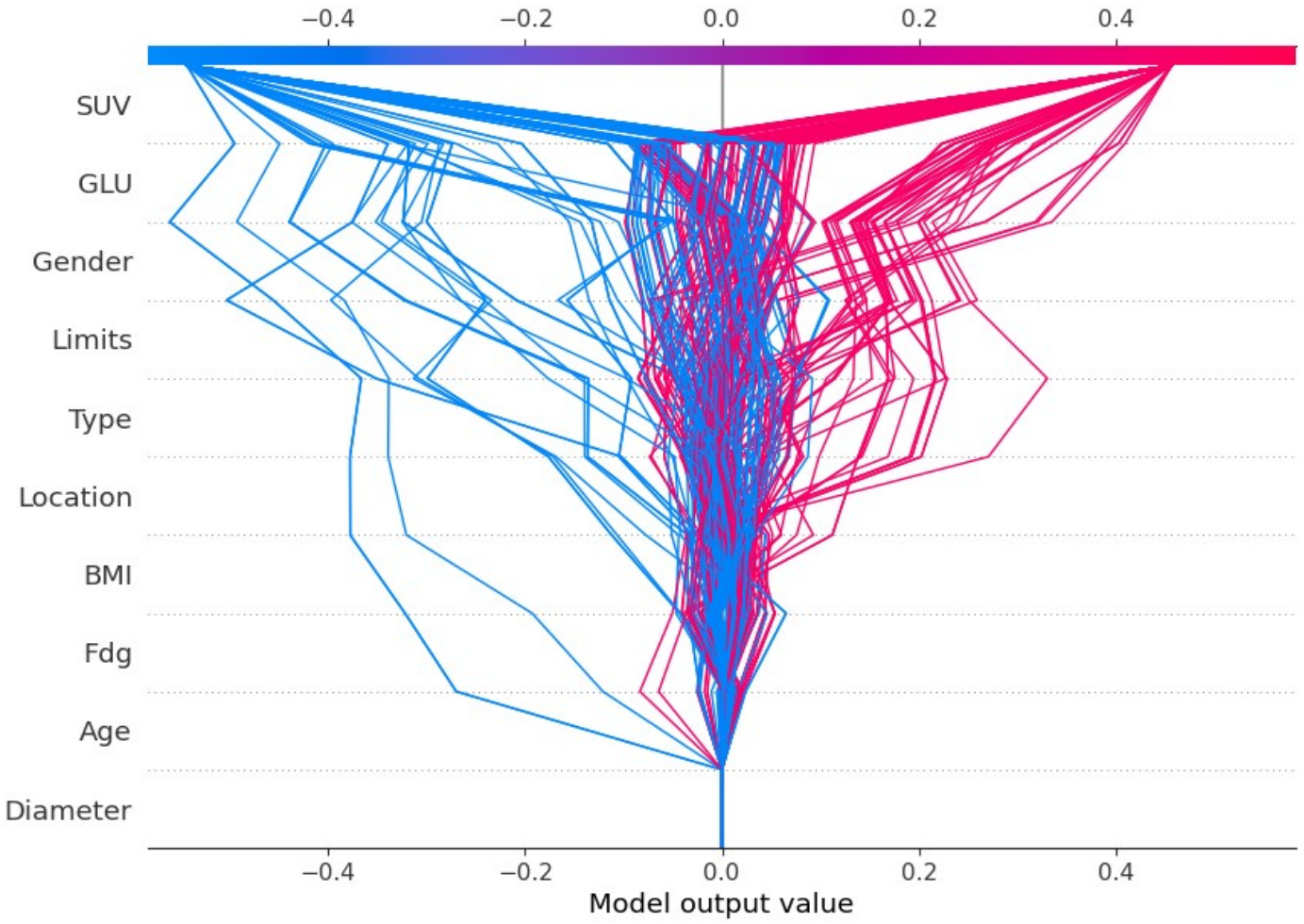
Order of performance ⬆

- AdaBoost
- Random Forest
- LightGBM
- TabPFN

Comparative Results



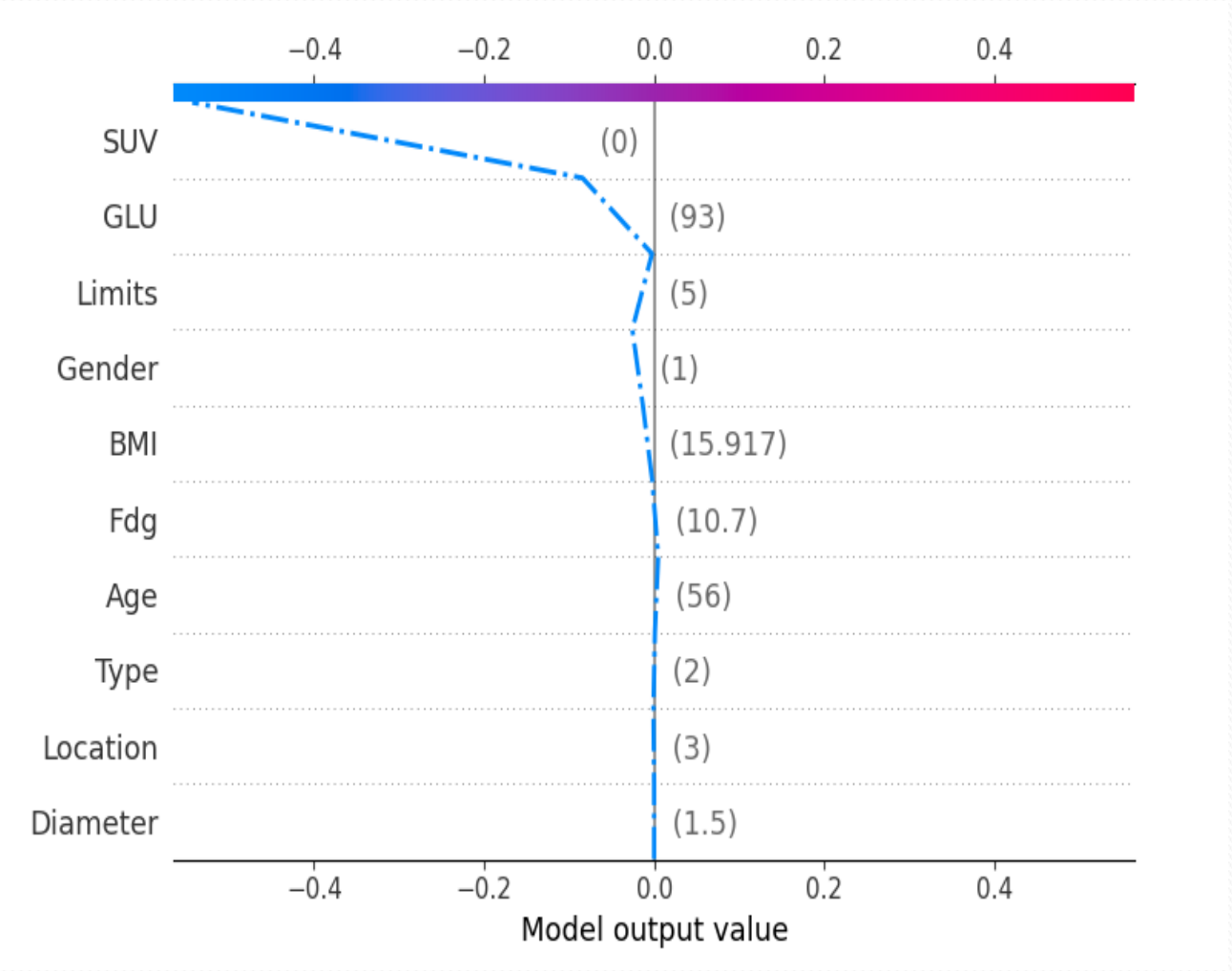
Explainability



Benign Case

Biggest Impact:

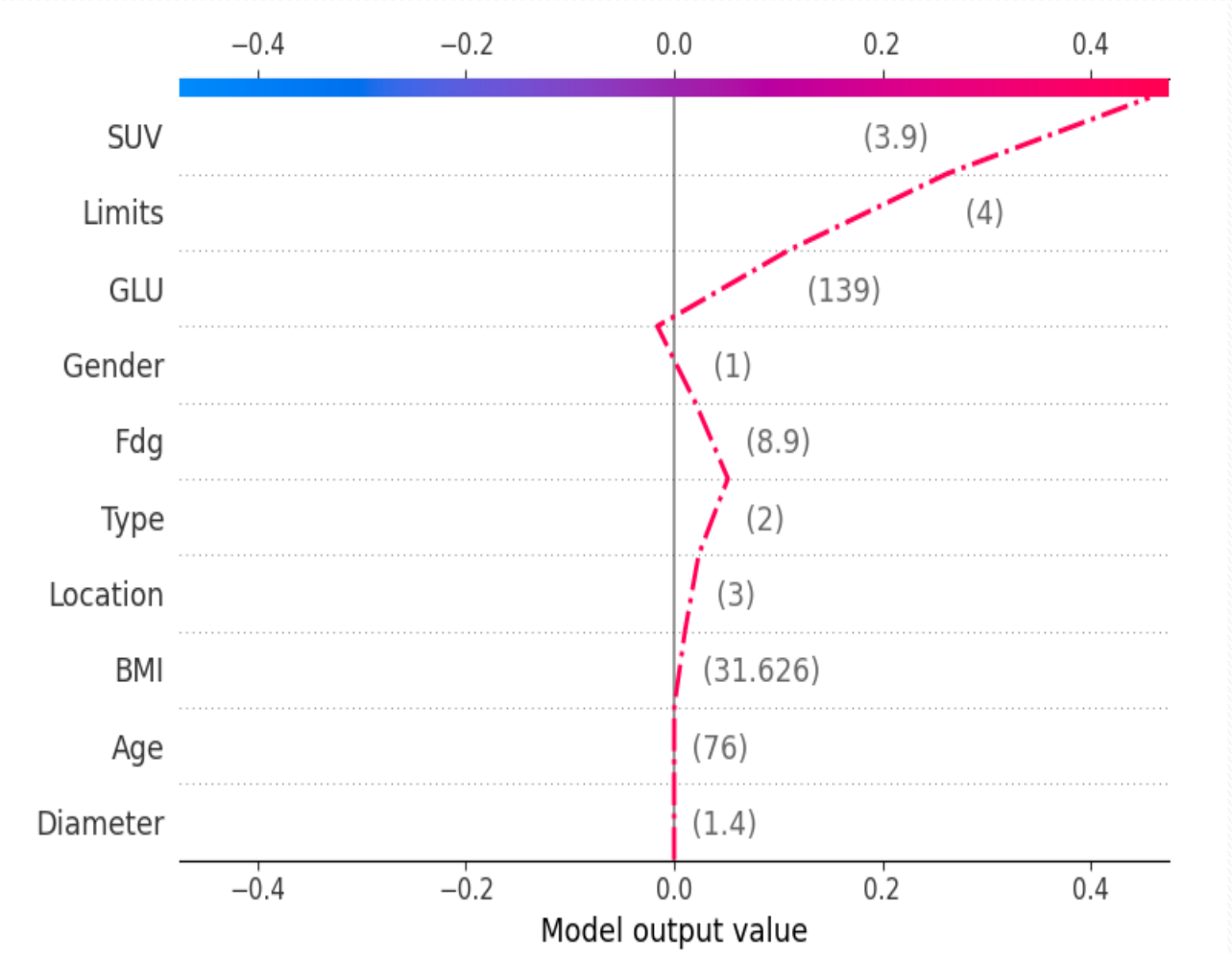
- SUV index (small value -> benign)
- GLU index (small value -> benign)
- Position of tumor (malignant)



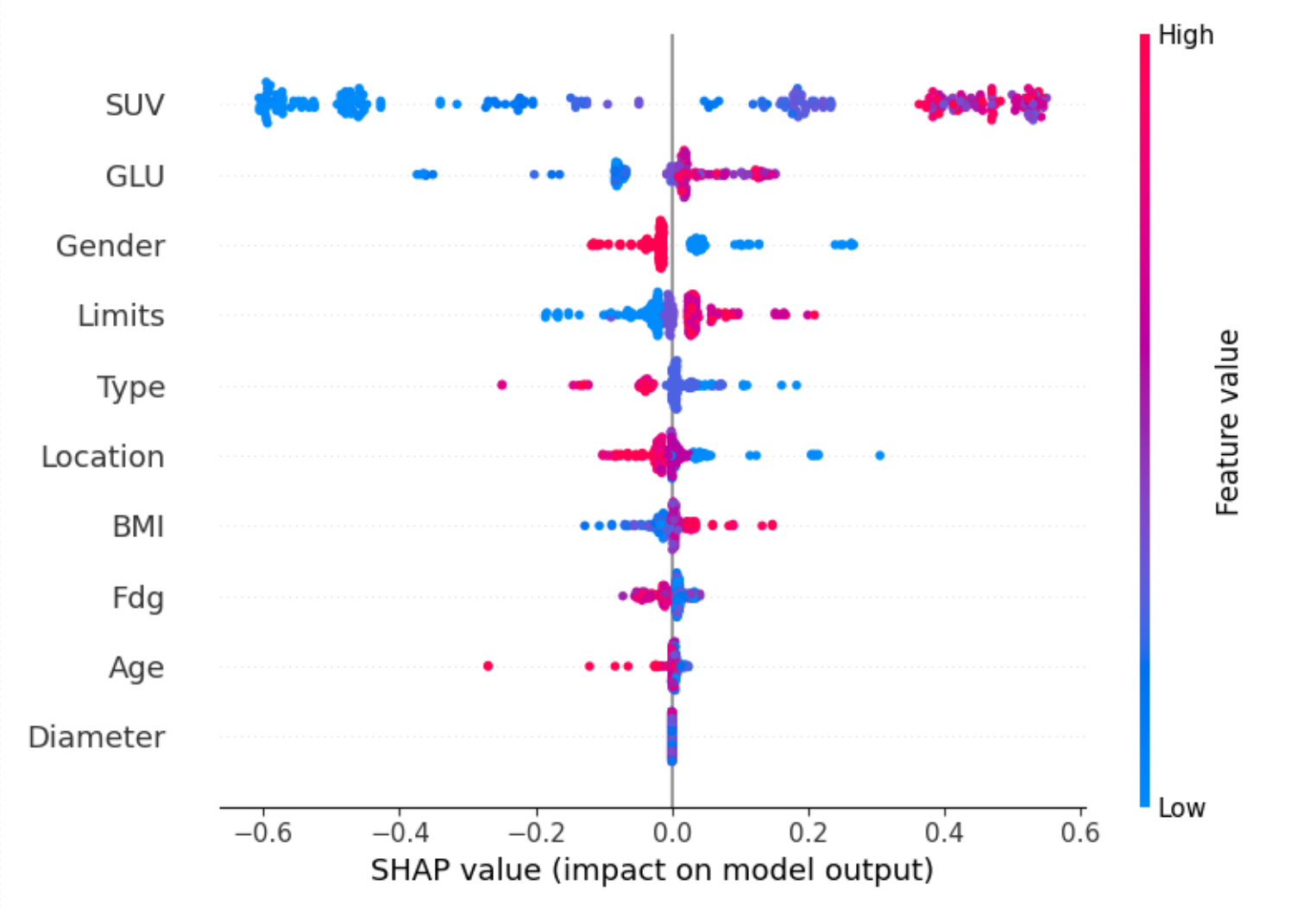
Malignant Case

Biggest Impact:

- SUV index (high value -> malignant)
- Position of tumor (malignant)
- GLU index (high value -> malignant)



Summary Plot



Conclusion

- Max achieved acc: 94.33%
- SUV uptake index - most impactful feature
- Explainability sheds light on the model's decision-making process
- Image data can possibly enhance the model


That's all Folks!
Any Questions?