CLASSIFICATION OF THORACIC SURGERY USING EXPLAINABLE AI

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Introduction

1. Thoracic surgery involves procedures related to the chest, including surgeries for lung cancer, esophageal disorders, and other thoracic conditions. The accurate classification of thoracic surgeries is crucial for treatment planning and patient outcomes.

2. Artificial Intelligence (AI) techniques, particularly machine learning, have shown promise in automating the classification process. By analyzing various data points such as patient demographics, medical history, imaging scans, and laboratory results, AI models can assist in classifying thoracic surgeries accurately..

3. In the context of medical applications like thoracic surgery classification, explainability is crucial for gaining trust and understanding from healthcare professionals. XAI techniques provide insights into how AI models arrive at their decisions, making the classification process transparent and interpretable.

Literature Review

- Wang et al. (2017) developed a deep convolutional neural network (CNN) for detecting pneumonia from chest X-rays, achieving an accuracy of 92.4%. Similarly, Lakhani and Sundaram (2017) employed a deep learning model to classify thoracic pathologies, including lung cancer, emphysema, and pulmonary fibrosis, from chest CT scans, with an overall accuracy of 87.6%.
- Huang et al. (2020), a combination of deep learning and radiomics features was utilized for the classification of lung cancer subtypes, achieving an accuracy of 93.2%. Meanwhile, Hosny et al. (2018) developed a deep learning model for the detection and classification of lung cancer from CT scans, with an accuracy of 94.4% in distinguishing between malignant and benign modules.
- Explainable AI (XAI) has emerged as a promising solution to address the interpretability challenge of machine learning models. XAI techniques aim to provide meaningful explanations for the decisions or predictions made by AI systems, enabling users to understand the reasoning behind the model's outputs. One powerful XAI technique is Local Interpretable Model-agnostic Explanations (LIME) (Ribeiro et al., 2016), which has been successfully applied in various domains, including computer vision and natural language processing.

Proposed Model

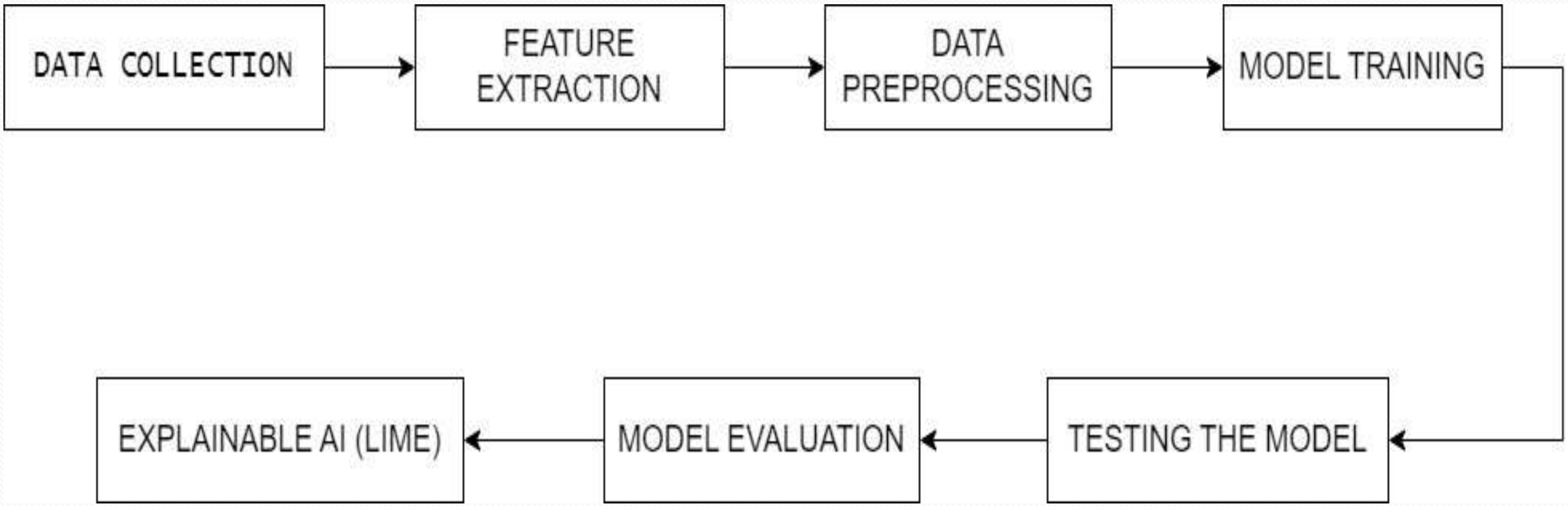


FIG: Proposed Model

Objectives

- Enhancing Trust: Build trust in the predictive models by providing transparent explanations for the predictions made in thoracic surgery classification.
- Interpretability: Enable clinicians and stakeholders to understand the factors contributing to the classification decisions, ensuring that the model's outputs are interpretable.
- Insight Generation: Gain insights into the key features and patterns driving the classification of different types of thoracic surgeries, aiding in medical decision-making.
- Education and Training: Serve as an educational tool for medical professionals, helping them understand the underlying principles of thoracic surgery classification and fostering continuous learning.
- Risk Assessment: Assess the risk factors associated with different types of thoracic surgeries, enabling personalized treatment plans and proactive management strategies.

Experimental Set-up

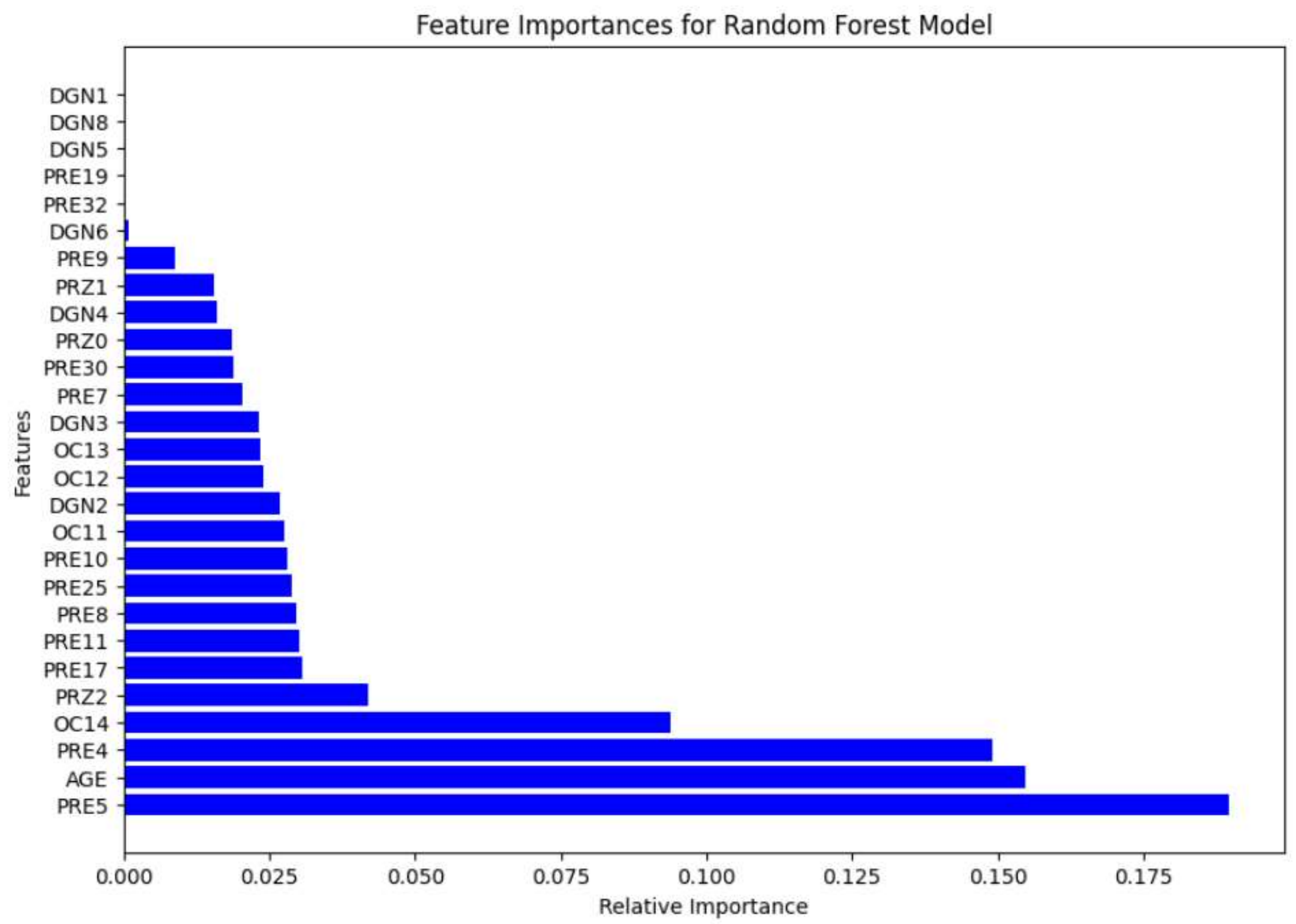
Software Requirements:

1. Python: The primary programming language for this project, employing libraries like Pandas, NumPy, Matplotlib, Bar Graph and Scikit-learn for data manipulation, analysis, visualization, and machine learning model development.
2. Jupiter Notebook and Colab : For coding, executing, and documenting the project workflow.
3. Specifically, for implementing LIME (Local Interpretable Model-agnostic Explanations) to achieve explainable AI insights

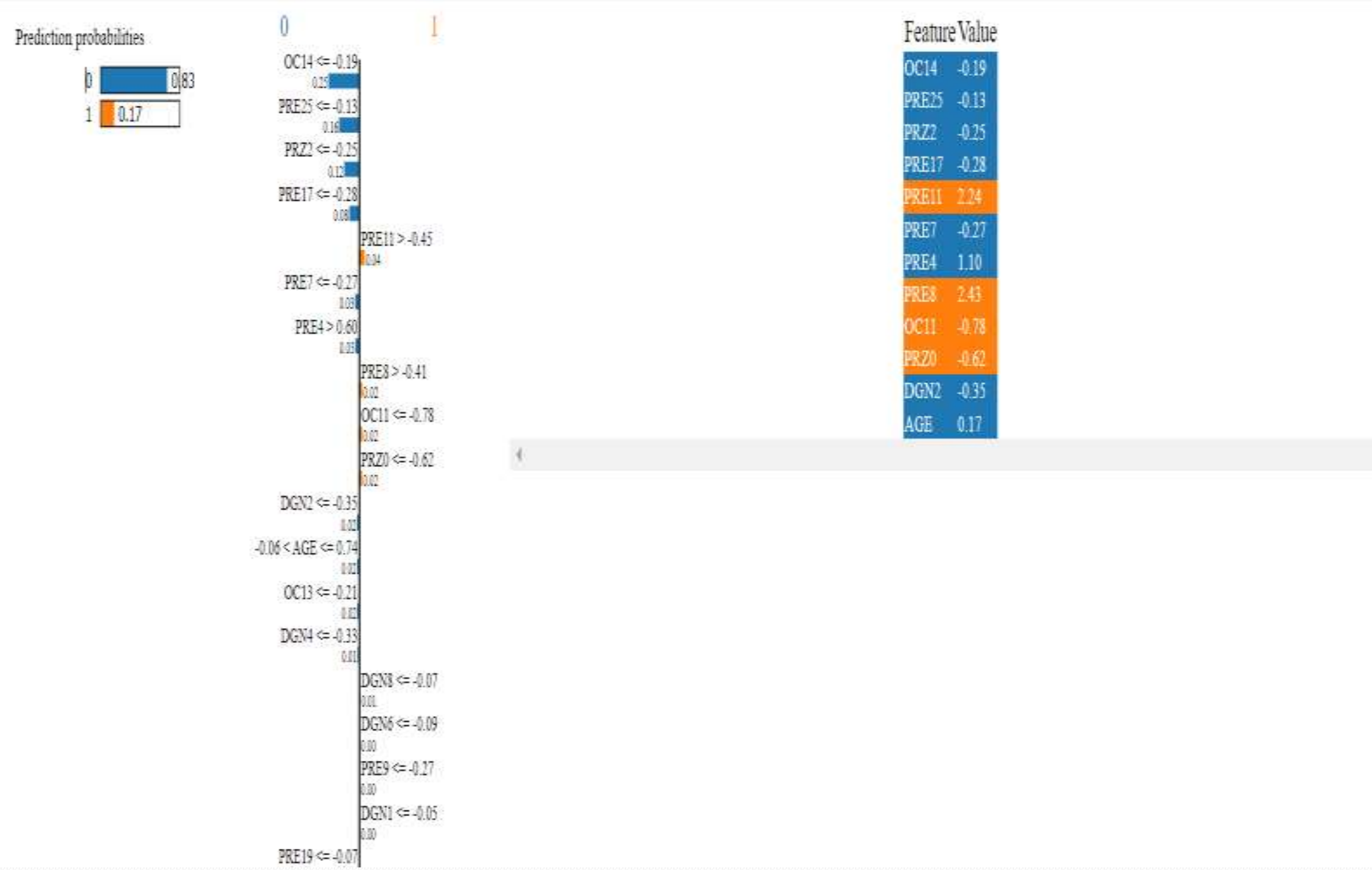
Modules Used:

1. Pandas and NumPy: For data preprocessing and manipulation.
2. Scikit-learn: For implementing the logistic regression model and other machine learning algorithms.
3. Matplotlib and Seaborn: For data visualization and plotting.
4. LIME: To provide explainable AI insights into the model's decision-making process.

Result



Feature Importances for Random Forest Model
Features
Relative Importance
DGN1
DGN8
DGN5
PRE19
PRE32
DGN6
PRE9
PRZ1
DGN4
PRZ0
PRE30
PRE7
DGN3
OC13
OC12
DGN2
OC11
PRE10
PRE25
PRE8
PRE11
PRE17
PRZ2
OC14
PRE4
AGE
PRE5
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175



Prediction probabilities
0 0.83
1 0.17
0
1
OC14 <= -0.19
0.25
PRE25 <= -0.13
0.16
PRZ2 <= -0.25
0.12
PRE17 <= -0.28
0.08
PRE11 > -0.45
0.04
PRE7 <= -0.27
0.03
PRE4 > 0.60
0.03
PRE8 > -0.41
0.02
OC11 <= -0.78
0.02
PRZ0 <= -0.62
0.02
DGN2 <= -0.35
0.02
-0.06 < AGE <= 0.74
0.02
OC13 <= -0.21
0.02
DGN4 <= -0.33
0.01
DGN8 <= -0.07
0.01
DGN6 <= -0.09
0.00
PRE9 <= -0.27
0.00
DGN1 <= -0.05
0.00
PRE19 <= -0.07
Feature Value
OC14 -0.19
PRE25 -0.13
PRZ2 -0.25
PRE17 -0.28
PRE11 2.24
PRE7 -0.27
PRE4 1.10
PRE8 2.43
OC11 -0.78
PRZ0 -0.62
DGN2 -0.35
AGE 0.17

Result Analysis

Model Performance:

- Accuracy: Provide the overall accuracy of the classification model on the test dataset.

Feature Importance:

- Identify the most important features contributing to the classification decision.
- Visualize feature importance using techniques like bar plots or heatmaps to highlight the relative significance of each feature.

Explainable AI:

- Finally, It will specify the final summazrized table of explanation including feature names, feature values and generates a visual representation of the LimeTabularExplainer's explanation, providing insights into how individual features contribute to the model's predictions.

Limitation

- Explainable AI techniques might struggle to provide comprehensible explanations for highly complex models, such as deep neural networks. If the classification model used for thoracic surgery is overly complex, the explanations provided might not be easily understandable by medical professionals or patients.
- Explainable AI techniques might not capture the full clinical context of thoracic surgery cases. They often rely on numerical features and might overlook important contextual information present in medical records, patient history, or imaging data.

Conclusions & Future Scope

- In Conclusion, Explainable AI models enable healthcare professionals to interpret and understand the factors influencing the classification of thoracic surgery cases. By identifying critical features, these models assist in accurate diagnosis and treatment planning.
- Through feature importance analysis, explainable AI reveals the key factors influencing the classification of thoracic surgery cases. This insight aids healthcare practitioners in focusing on the most relevant clinical indicators for effective decision-making.
- By uncovering the rationale behind predictions, explainable AI helps in identifying potential errors or biases in the classification process. This awareness enables proactive measures to mitigate risks and improve patient outcomes.
- In future we are thinking of add more features and models to make it more accurate

References

- Explainable AI Recipes: Implement Solutions to Model Explainability and Interpretability with Python - Pradeepta Mishrahttps://doi.org/10.1007/978-1-4842-9029-3

- Explainable AI (XAI) has emerged as a promising solution to address the interpretability challenge of machine learning models.


Thank You!