# 919P ARTIFICIAL INTELLIGENCE SUPPORTING LUNG CANCER SCREENING: COMPUTER AIDED DIAGNOSIS OF LUNG LESIONS DRIVEN BY MORPHOLOGICAL FEATURE EXTRACTION

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## BACKGROUND

Lung Cancer is among the most common cancer types, and is the leading cause of cancer deaths worldwide. Despite the expansion of the eligible US population after the updated USPSTF guidelines in 2021, lung cancer screening penetration remains low with average inclusion rates in 2020 of 6.5%. These low inclusion rates are caused by a number of barriers imposed by patients and providers alike. Although slow in their implementation into the lung screening routine, Artificial Intelligence (AI) tech-based diagnostics stand to help remove these barriers by providing more accurate image analysis and patient management.

## METHODS

An “end-to-end” model designed to detect and characterize the malignancy risk of suspicious pulmonary lesions found on LDCT lung screening scans. The model uses a LDCT as input and provides the location and risk probability for each lesion detected in the scan. The model was trained (lesions: 388 Cancer, 12.332 Benign) and tested (lesions: 153 Cancer, 4.531 Benign) on a subset of the NLST dataset for which lesions were annotated by a team of radiologists. Given that AI explainability is often cited as a concern to clinicians, an evaluation of the clinical parameters that influenced the predictions of the models was performed.

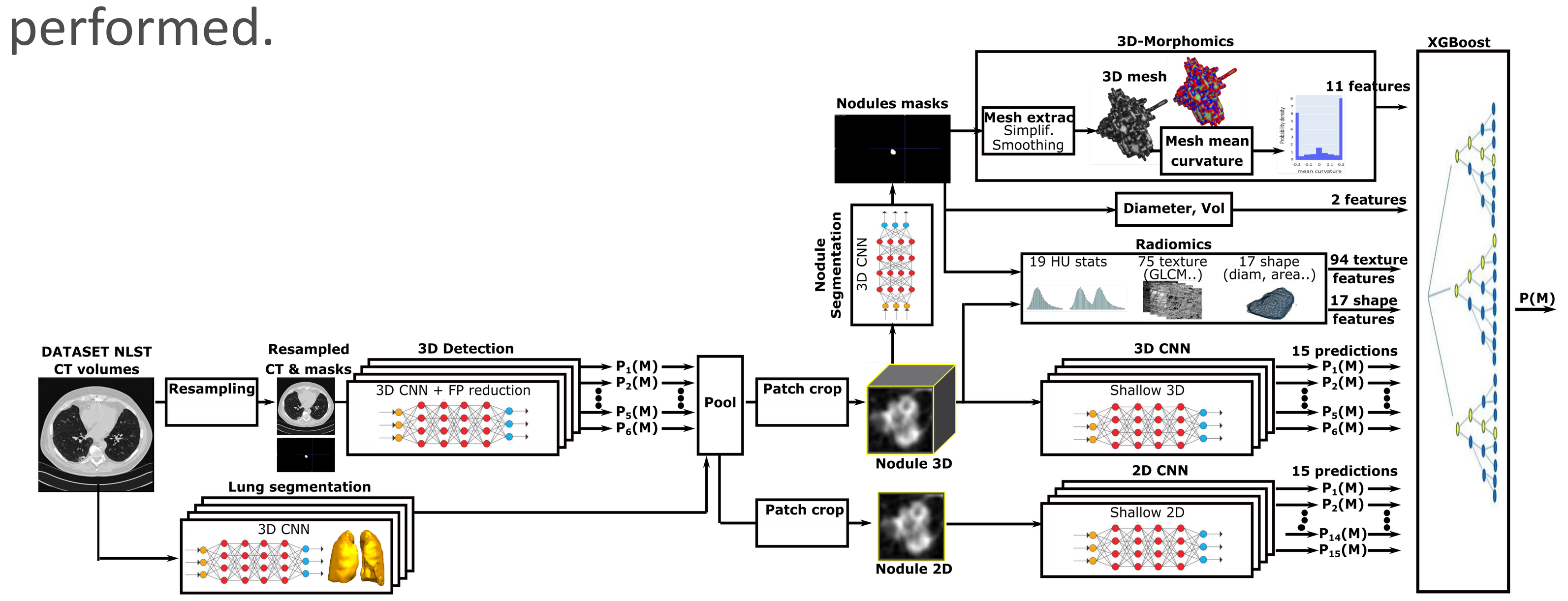


**Figure 1:** Presentation of the global workflow of the CADe/Cadx for lesion prediction, with CADe 3D CNN detection on the left, and with CADx on the right. The CADx ensembles 3 different predictors: 3D and 2D CNN models [1,3], and Radiomics and 3D-morphomics features [2,4].

## RESULTS

When using a size threshold of 3mm maximal axial diameter the overall lesion level performance of the combined detection and characterization reached an AUC of 0.964 with 92.1% sensitivity and 95.9% specificity, with a mean AUC 0.965+/-0.011 stdev and a 95% CI of [0.941 0.985] using 5000 bootstrap samples. Lesion detection performance was 90.0% sensitivity with an average of 9.8 false positive detections per scan. Results of the clinical feature importance shows that the top 40 features accounting for the models prediction were composed of 27 deep Convolutional Neural Network (CNN) predictions, 7 nodule shape features (Maximum 2D axial diameter, maximum 2D coronal diameter, maximum 2D sagittal diameter, spiculation, margins, VoxelVolume and volume) and HU texture radiomics (SizeZoneNonUniformity, TotalEnergy, DependanceNonUniformity).

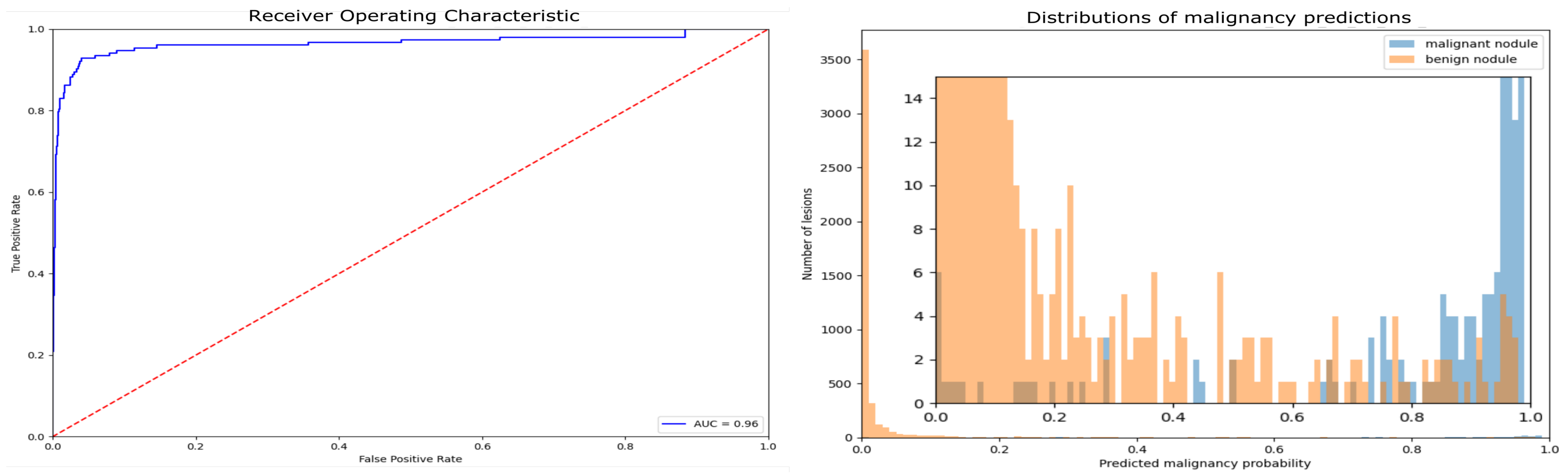


**Figure 2:** The ROC curve (left) and the distribution of malignancy prediction (right) for the 40 best features of 2D+3D+3D-morphoradiomic ensemble model on the 473 patients test set with an enlarged view on the low occurrence values of the distribution.

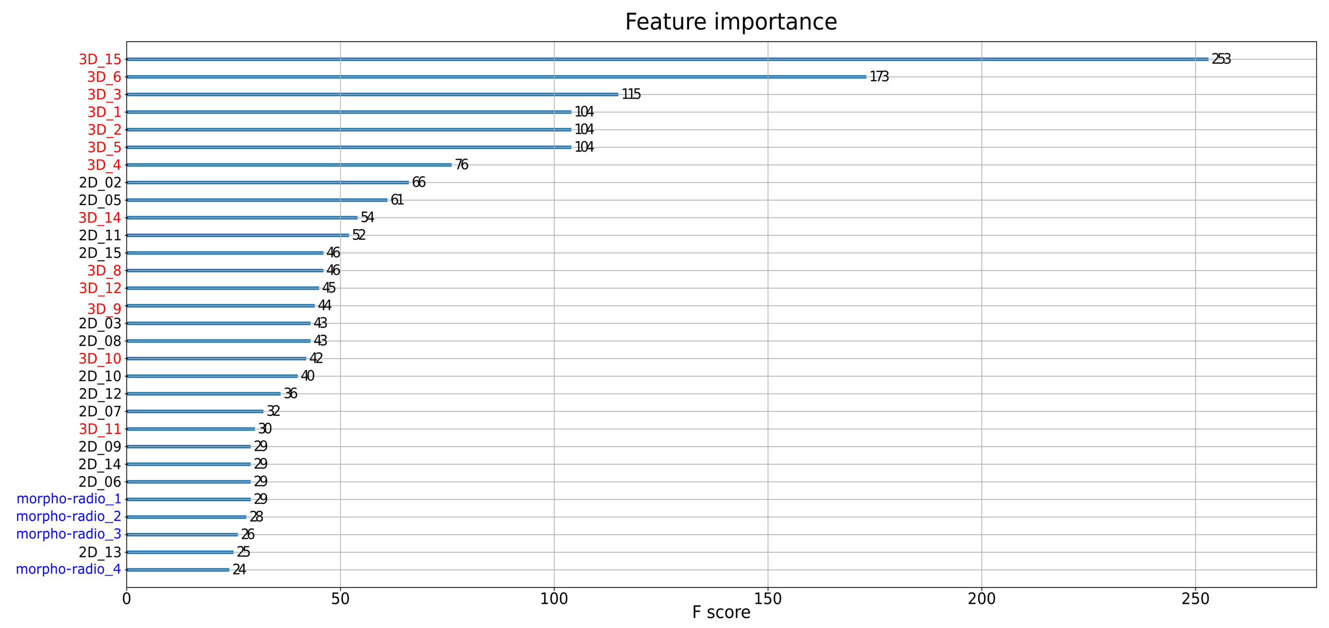


**Figure 3:** .Importance of the 30 first highest predictive features-variables (out of the 40 out of a total of 152 features) using XGBoost. The 40 best features are composed of: 13 (out of 15) 3D-CNN predictions, 14 (out of 15) 2D-CNN predictions, 5 (out of 94) texture radiomics quantifying attenuation, 4 (out of 17) shape radiomics all quantifying nodule size and volume (2 diameters and 2 volumes), and 3 (out of 11) 3D-morphomics quantifying margins, spiculations.

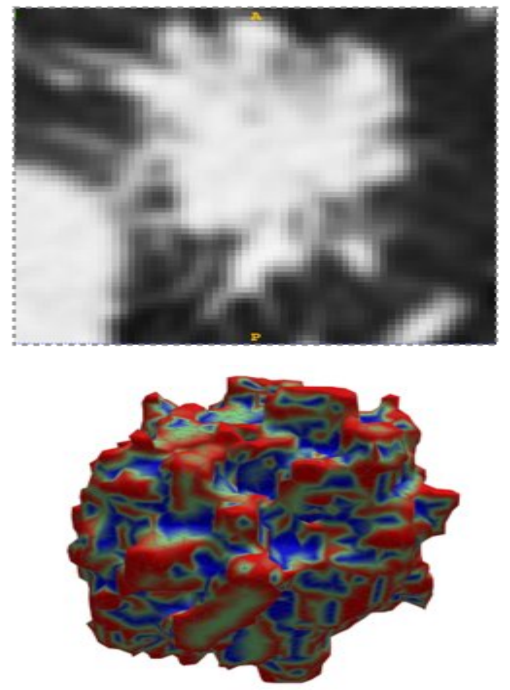

Figure 4: Example of a malignant nodule (top) and its corresponding 3D mesh (bottom). The mean curvature values are color coded from blue-negative, green-close to zeros, red-positive.

## CONCLUSIONS

Here, we present the evaluation of an AI/ML tech based computer aided detection and characterization (CADe/CADx) with high performances and low false positives. The features of importance for the models were largely based off of deep Convolutional Neural Network predictions and were only partially driven by more classical morphological feature extractions.

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