## Appendix-1

#### **Section 1: Radiomic Feature Extraction.**

Lung nodules were annotated by an expert radiologist using 3D-slicer (3D Slicer, version 4.6: NIH-funded; <a href="https://www.slicer.org">https://www.slicer.org</a>) and a freehand tool. Intratumoral and peritumoral areas were selected using these annotations. For intratumoral region, the annotated tumor is used as the area of interest. Following annotations, the peritumoral region corresponding to the lesion was defined using the following steps. Firstly, a morphological operation of dilation was performed to capture the area outside the nodule, up to a radial distance of 15mm from the lesion boundary. The choice of peri-nodular size was based on previous findings, where a resection margin >15mm did not have a prognostic effect in the context of disease recurrence. The intranodular mask was then subtracted from this dilated mask to obtain a ring of lung parenchyma immediately around the nodule. The perinodular region was subsequently divided into five equally spaced 3-mm rings.

Radiomic features were extracted from the three slices having the maximum area of the tumor using software developed in the Center of Computational Imaging and Personalized Diagnostics, Case Western Reserve University, implemented on a MATLAB release 2016a platform (MathWorks, Natick, MA, USA).

A total of 124 textural descriptors were commutated voxel-wise across the three slices from each of the annotated region. The features included 48 from Gabor feature family, 13 from Haralick, 13 from Collage, 25 from Laws, and 25 from Laplace feature families. The First-order statistics (mean, median, SD, skewness, and kurtosis) were calculated from each feature vector. Table-S1 explains all the extracted features.

#### **Section 2: QVT feature Extraction**

The segmented nodule and the 3D segmented vasculature surrounding the nodule were used for extracting vessel tortuosity features (QVT). The vasculature surrounding the nodule was segmented using a region growing algorithm by using an initial seed point. A fast-marching algorithm was then employed to identify the center lines of the 3D segmented vasculature. A set of 74 QVT features were then measured form points, branches, and the entire vasculature centerlines. These features pertain to the tortuosity, curvature and branching statistics as well as the volume of the vasculature. In addition, we measured the angles of each three consecutive points of the vasculature and computed the distribution of these angles.

A total of 74 QVT features were extracted for each patient, representing the curvature and tortuosity of the nodule associated vessels and their branching statistics.

#### **Section 3: Total Extracted Radiomic Features.**

**Table S.1** – Total Radiomic Features extracted from intratumoral and annular ring-shaped peritumoral regions. A total of 6 statistics- (mean, median, kurtosis, skewness, standard deviation, and range) were calculated for each feature.

Radiomic Feature Family	Radiomic Feature Parameters	Radiomic Feature Family	Radiomic Feature Parameters
	Entropy, Window Size = 5		Level, Level
	Energy, Window Size = 5		Level, Edge
	Inertia, Window Size = 5		Level, Spot
	Inverse Difference Moment , Window Size = 5		Level, Wave
	Correlation, Window Size = 5	T	Level, Ripple
Haralick	Information Measure of Correlation-1, Window Size = 5	on Measure of Correlation-1, Window Size = 5	
Feature	Information Measure of Correlation-2, Window Size = 5  Feature		Edge, Edge
Family	Sum Average, Window Size = 5	Family	Edge, Spot
	Sum Variance, Window Size = 5		Edge, Wave
	Sum Entropy, Window Size = 5		Edge, Ripple
	Difference Average, Window Size = 5		Spot, Level
	Difference Variance, Window Size = 5		Spot, Edge
	Difference Entropy, Window Size = 5		Spot, Spot

	Orientation=0, Bandwidth=1, Frequency=0		Spot, Wave
ŀ	Orientation=0, Bandwidth=1, Frequency=2		Spot, Ripple
ļ.	Orientation=0, Bandwidth=1, Frequency=4		Wave, Level
ļ.	Orientation=0, Bandwidth=1, Frequency=6		Wave, Edge
ŀ	Orientation=0, Bandwidth=1, Frequency=8		Wave, Spot
F	Orientation=0, Bandwidth=1, Frequency=10		Wave, Wave
F	Orientation=π/8, Bandwidth=1, Frequency=0		Wave, Ripple
-	Orientation=π/8, Bandwidth=1, Frequency=2	=	Ripple, Level
-	Orientation=π/8, Bandwidth=1, Frequency=4	=	Ripple, Edge
-	Orientation=π/8, Bandwidth=1, Frequency=6	=	Ripple, Spot
-	Orientation=π/8, Bandwidth=1, Frequency=8	_	Ripple, Wave
	Orientation=π/8, Bandwidth=1, Frequency=10		Ripple, Ripple
-	Orientation=π/4, Bandwidth=1, Frequency=0		Level, Level
-	Orientation=π/4, Bandwidth=1, Frequency=2		Level, Edge
-			
-	Orientation=π/4, Bandwidth=1, Frequency=4		Level, Spot
-	Orientation=π/4, Bandwidth=1, Frequency=6	_	Level, Wave
-	Orientation=π/4, Bandwidth=1, Frequency=8	_	Level, Ripple
-	Orientation=π/4, Bandwidth=1, Frequency=10	_	Edge, Level
-	Orientation=3π/8, Bandwidth=1, Frequency=0	_	Edge, Edge
	Orientation=3π/8, Bandwidth=1, Frequency=2		Edge, Spot
-	Orientation=3π/8, Bandwidth=1, Frequency=4		Edge, Wave
-	Orientation=3π/8, Bandwidth=1, Frequency=6		Edge, Ripple
Gabor	Orientation=3π/8, Bandwidth=1, Frequency=8		Spot, Level
Wavelet	Orientation=3π/8, Bandwidth=1, Frequency=10	Laplace	Spot, Edge
Feature	Orientation=π/2, Bandwidth=1, Frequency=0	Feature	Spot, Spot
Family	Orientation=π/2, Bandwidth=1, Frequency=2	Family	Spot, Wave
	Orientation=π/2, Bandwidth=1, Frequency=4		Spot, Ripple
	Orientation=π/2, Bandwidth=1, Frequency=6		Wave, Level
	Orientation=π/2, Bandwidth=1, Frequency=8		Wave, Edge
	Orientation=π/2, Bandwidth=1, Frequency=10		Wave, Spot
	Orientation=5π/8, Bandwidth=1, Frequency=0		Wave, Wave
	Orientation=5π/8, Bandwidth=1, Frequency=2		Wave, Ripple
	Orientation=5π/8, Bandwidth=1, Frequency=4		Ripple, Level
	Orientation=5π/8, Bandwidth=1, Frequency=6		Ripple, Edge
	Orientation=5π/8, Bandwidth=1, Frequency=8		Ripple, Spot
	Orientation=5π/8, Bandwidth=1, Frequency=10		Ripple, Wave
	Orientation=3π/4, Bandwidth=1, Frequency=0		Ripple, Ripple
	Orientation=3π/4, Bandwidth=1, Frequency=2		Entropy, Window Size = 5
	Orientation=3π/4, Bandwidth=1, Frequency=4		Energy, Window Size = 5
	Orientation=3π/4, Bandwidth=1, Frequency=6		Inertia, Window Size = 5
	Orientation=3π/4, Bandwidth=1, Frequency=8		Inverse Difference Moment , Window Size = 5
	Orientation=3π/4, Bandwidth=1, Frequency=10		Correlation, Window Size = 5
	Orientation=7π/8, Bandwidth=1, Frequency=0	CoLIAGe	Information Measure of Correlation-1, Window Size = 5
ļ	Orientation=7π/8, Bandwidth=1, Frequency=2	Feature	Information Measure of Correlation-2, Window Size = 5
ļ	Orientation=7π/8, Bandwidth=1, Frequency=4	Family	Sum Average, Window Size = 5
ļ	Orientation=7π/8, Bandwidth=1, Frequency=6	٠ -	Sum Variance, Window Size = 5
ļ	Orientation=7π/8, Bandwidth=1, Frequency=8	1	Sum Entropy, Window Size = 5
	Orientation=7π/8, Bandwidth=1, Frequency=10	1	Difference Average, Window Size = 5
		•	
-			Difference Variance, Window Size = 5

## **Section 4: Radiomic Feature Stability.**

Feature stability and reproducibility were evaluated using the RIDER test-retest dataset. This dataset had 31 lung cancer patients, scanned two times with 15 mins' difference apart. Two scans of every patient were used for calculating the intraclass correlation coefficient (ICC) for each feature vector. Considering the threshold of 0.85, the analysis was performed using all feature vectors having ICC values higher than the threshold limit. After completing the above experiment, a total of 757 features were retained from the intratumoral and peritumoral feature pool of 4464. These stable features were used for further analysis for feature selection and model building.

#### **Section 5: Tumor Growth Kinetics.**

Target lesions were identified and assessed on each interval CT scan using the RECIST version 1.1 criteria (Eisenhaur et al). A sum of diameters (SOD) of the target lesions pre- baseline (SODpre), baseline (SODbaseline) and post ICI (SODpost) was calculated. Using a previously described methodology to calculate tumor growth kinetics, the rate of change in the dimensions of target lesions pre and post-therapy was calculated (Le Tourneau at al, Saada et al). Tumor growth kinetics pre-therapy (TGKpre) was defined as SODbaseline – SODpre/Timebaseline-Timepre. Similarly, TGK post ICI (TGKpost)= SODpost-SODbaseline/Timepost-Timebaseline.

Hyperprogressive disease was defined as

- 1. Time to treatment failure < 9 weeks (or 3-cycles)
- 2. Progressive disease on first radiographic assessment after ICIs
- 3. Greater than two-fold increase in tumor growth kinetics after initiating immune checkpoint blockade (TGKpost:  $TGKpre \ge 2$ )

### Section 6: CT Scan parameters.

**Table S.2** – CT scan parameters

	No. of studies = 109	Kernal
Siemens	75	B30f, B31f, B31s, B35f, B35s, B41f, B60f, B60s, B70f, I40f\(^2\), I50f\(^1\)
Philips	20	B, C, D, L, YA, YB
Toshiba	1	FC52
GE	12	Lung, SOFT, Standard
<=1	9	
<1<=3	89	
3< <=5	10	
With Contrast	89	
W/o Contrast	20	

### Section 7: Unsupervised cluster validations

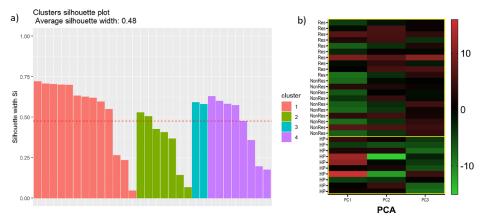


Fig S1: Validation of unsupervised clustering maps with a) silhouette coefficients and b) heatmaps

## **Section 8: Top Features.**

Top features selected using minimum redundancy maximum relevance (mRMR) feature selection method. The number of top features were restricted to 3 to avoid potential overfitting.

**Table S.3** – Top selected features

	Feature Family		Descriptor	Location	Statistics
1	QVT7	Mean Curvature of branches surrounding the tumor	Mean	Surrounding the tumor	Mean
2	QVT44	Curvature values associated with vasculature	Entropy	Intratumoral	Mean
3	Radiomics	Gabor	Freq-π/2 theta-90	5-10mm	Median

### **Section 9: Correlation.**

The selected top features were compared against clinical features with pearson's correlation coefficien. Further the tumor volume was computed and correlation coefficient was calculated between radiomic top features and tumor volume. The following graph shows correlation coefficients between these variables. The maximum correlation was observed between Radiomics Gabor feature and tumor volume which was 0.588.

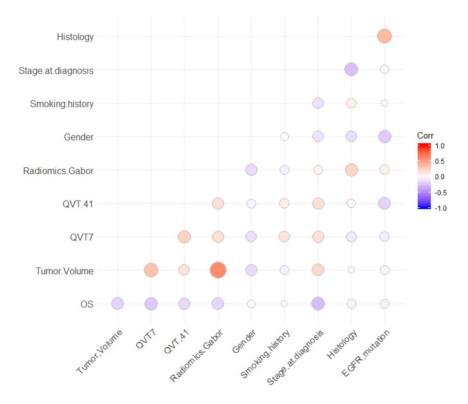


Fig S2: Pearson's Correlation coefficients between Radiomics Top Features and clinical variables.

## Section 9: Distribution of Patients within Training and Testing Sets

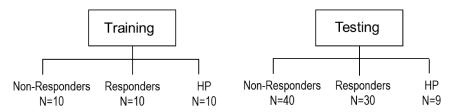


Fig S3: Distribution of patients into training and testing set

# Section 9: Classifier Performance on Training Set

#### Feature Selection Method: mRMR

**Table S.4** – Classifier performances on training set

	Classifier	AUC	Accuracy	Specificity	Sensitivity
1	<u>RF</u>	$0.85 \pm 0.06$	$0.86 \pm 0.06$	$0.91 \pm 0.10$	$0.78 \pm 0.11$
2	LDA	$0.80 \pm 0.07$	$0.82 \pm 0.07$	$0.86 \pm 0.11$	$0.75 \pm 0.13$
3	DLDA	$0.81 \pm 0.08$	$0.83 \pm 0.06$	$0.88 \pm 0.10$	$0.74 \pm 0.13$
4	QDA	$0.75 \pm 0.11$	$0.81 \pm 0.06$	$0.89 \pm 0.09$	$0.68 \pm 0.16$
5	DQDA	$0.50 \pm 0.00$	$0.63 \pm 0.00$	$1.00 \pm 0.00$	$0.00 \pm 0.00$
6	SVM	$0.81 \pm 0.06$	$0.83 \pm 0.06$	$0.87 \pm 0.11$	$0.76 \pm 0.12$

## **Section 10: Classifier Performance on Test Set**

Table S.4 – Classifier performances on test set

	Accuracy	Specificity
1	AUC	0.96
2	Accuracy	0.83
3	TP	9
4	TN	57
5	FP	13
6	FN	0
7	F1 Score	0.58