Supplementary Materials

Multi-classifier-based Identification of COVID-19 from Chest CT using Generalizable and Interpretable Radiomics Features

Appendix A: CT scanning parameters

In the study population, patients from the hospitals in China were imaged with a CT slice of 1-mm thickness on a GE Revolution 256 scanner (GE Medical Systems, Waukesha, USA), or imaged with a CT slice of 5-mm thickness on a NeuViz 128 scanner (Neusoft, Shenyang, China), or with a CT slice of 5-mm thickness on a NeuViz 64 scanner (Neusoft, Shenyang, China).

CT scans of the patients from the hospital from the United States were obtained at 1-3 mm slice thickness with or without contrast (Lightspeed VCT and Revolution, GE Healthcare, Milwaukee, WI; Aquilion, Toshiba Medical Systems, Otawara, Japan; SOMATOM, Siemens Healthineers, Erlangen, Germany). CT images were reviewed by radiologists at each center having more than ten years of individual experience.

Appendix B: Samples of the manually segmentation of pneumonia lesions

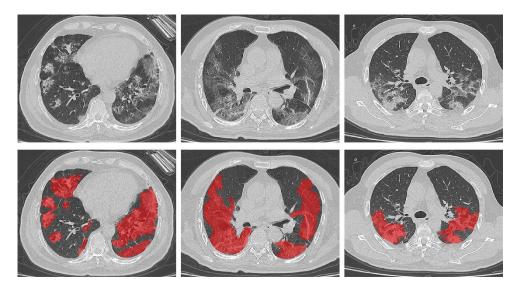


Figure S1. The mask of the region of interest of SARS-CoV-2 positive pneumonia lesions which manually segmented by radiologists. The three CT slices were from different patients.

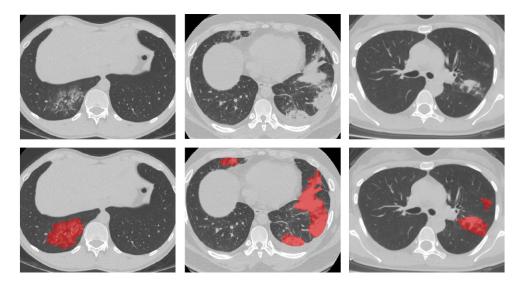


Figure S2. The mask of the region of interest of SARS-CoV-2 negative pneumonia lesions which manually segmented by radiologists. The three CT slices were from different patients.

Appendix C: Selected significant radiomics features by each classifier

 $Lasso\ Classifier = 3.653673$

+ 4.958981e-03 * diagnostics_Image-original_Mean +

-4.263274e-05 * diagnostics_Image-original_Minimum +

3.322157e-01 * diagnostics Mask-original VolumeNum +

3.989302e-03 * original shape MajorAxisLength +

1.870174e-03 * original shape Maximum2DDiameterColumn +

-1.788563e-02 * original shape SurfaceVolumeRatio +

-1.297587e-04 * original firstorder RootMeanSquared +

2.658778e-01 * original firstorder Skewness +

-1.333541e+01 * original_firstorder_Uniformity +

1.022123e-03 * original glcm Contrast +

1.067405 * original gldm DependenceNonUniformityNormalized +

-7.053722 * original_gldm_LowGrayLevelEmphasis +

2.146219e-05 * original gldm SmallDependenceHighGrayLevelEmphasis +

-7.310696 * original_gldm_SmallDependenceLowGrayLevelEmphasis +

 $-1.707699e-01*original_glrlm_ShortRunLowGrayLevelEmphasis+\\$

 $-6.043230e - 05* original_glszm_LargeAreaHighGrayLevelEmphasis + \\$

 $-8.216791e\hbox{-}01*original_ngtdm_Busyness$

Linear classifier (p < 0.0001):

[1] diagnostics Image-original Mean

- [2] diagnostics Mask-original VoxelNum
- [3] diagnostics_Mask-original_VolumeNum
- [4] original shape Maximum2DDiameterSlice
- [5] original shape MeshVolume
- [6] original_shape_Sphericity
- [7] original shape SurfaceArea
- [8] original_firstorder_Entropy
- [9] original_firstorder_InterquartileRange
- [10] original_firstorder_MeanAbsoluteDeviation
- [11] original firstorder Minimum
- [12] original firstorder RobustMeanAbsoluteDeviation
- [13] original firstorder RootMeanSquared
- [14] original glcm_DifferenceEntropy
- [15] original glcm Id
- [16] original_glcm_Idm
- [17] original glcm Imc2
- [18] original glcm InverseVariance
- [19] original glcm JointAverage
- [20] original_glcm_SumEntropy
- [21] original_gldm_DependenceEntropy
- [22] original gldm GrayLevelNonUniformity
- [23] original glrlm GrayLevelNonUniformity

- [24] original glrlm RunEntropy
- [25] original glszm GrayLevelNonUniformity
- [26] original firstorder Uniformity

Least absolute shrinkage and selection operator (lambda.min):

- [1] diagnostics_Image-original_Mean
- [2] diagnostics_Image-original_Minimum
- [3] diagnostics_Mask-original_VolumeNum
- [4] original shape MajorAxisLength
- [5] original shape Maximum2DDiameterColumn
- [6] original shape SurfaceVolumeRatio
- [7] original firstorder RootMeanSquared
- [8] original firstorder Skewness
- [9] original firstorder Uniformity
- [10] original glcm_Contrast
- [11] original gldm DependenceNonUniformityNormalized
- [12] original gldm LowGrayLevelEmphasis
- [13] original gldm SmallDependenceHighGrayLevelEmphasis
- [14] original_gldm_SmallDependenceLowGrayLevelEmphasis
- [15] original glrlm ShortRunLowGrayLevelEmphasis
- [16] original glszm LargeAreaHighGrayLevelEmphasis
- [17] original ngtdm Busyness

Random forest (Top-20 features of significance):

- 1. diagnostics Image-original Mean
- 2. original_glrlm_ShortRunLowGrayLevelEmphasis
- 3. original glrlm LowGrayLevelRunEmphasis
- 4. original_gldm_LowGrayLevelEmphasis
- 5. original glszm LowGrayLevelZoneEmphasis
- 6. original shape Maximum2DDiameterSlice
- 7. original firstorder Median
- 8. original shape Maximum3DDiameter
- 9. original shape MajorAxisLength
- 10. original ngtdm Coarseness
- 11. original gldm LargeDependenceHighGrayLevelEmphasis
- 12. diagnostics Image-original Maximum
- 13. original_firstorder_RootMeanSquared
- 14. diagnostics Image-original Minimum
- 15. original shape Maximum2DDiameterColumn
- 16. original glszm ZoneVariance
- 17. original_firstorder_10Percentile
- 18. original_firstorder_Uniformity
- 19. diagnostics Mask-original VolumeNum
- 20. original firstorder Minimum

Appendix D: The procedure of radiomics model training by LASSO

The R language was used to construct the LASSO radiomics classifier based on the features extracted by Pyradiomics, and the construction of other classifiers is similar to this process. First, we input the COVID-19 status of each image (1 meant positive and 0 meant negative) and the corresponding 120-dimensional radiomics feature of each image into R. Then, the "glmnet" and "cv.glmnet" functions were used to obtain the coefficients of each feature by LASSO classifier and the final LASSO model, respectively. Finally, the LASSO radiomics model was further tested.

The above-mentioned well-trained LASSO radiomics model is included as supplementary study data. Please use the command "load()" to reuse the model. The source code of this algorithm is shown below.

```
y<- TrainData$COVID_Status

TrainData_Feature_Lasso <- TrainData$Feature

names(TrainData_Feature_Lasso) <- NULL

TrainData_Feature_Lasso <-data.matrix(TrainData_Feature_Lasso)

fit<-glmnet(TrainData_Feature_Lasso,y,alpha=1,family='binomial')

cv.fit<-cv.glmnet(TrainData_Feature_Lasso,y,family="binomial")

Test <-predict(fit,type="response",newx = Test_Feature,s=cv.fit$lambda.1se)

Roc_Test<-roc(TestData$COVID_Status, Test)

auc(Roc_Test)
```