

CLAIMS

1. A method for predicting one or more future risks of lung cancer for a subject, the method comprising:
obtaining one or more images captured from the subject at a single timepoint;
extracting features from the one or more obtained images, the extracted features comprising at least non-nodule specific features, wherein the non-nodule specific features comprise one or both of lung parenchyma features or body composition features;
predicting one or more future risks of lung cancer for the subject by applying one or more trained risk prediction models to analyze the extracted features from the one or more obtained images.
2. The method of claim 1, wherein predicting the one or more future risks of lung cancer for the subject comprises applying a M year risk prediction model to predict whether the subject is likely to develop lung cancer within M years, wherein the M year risk prediction model comprises nodule specific features and non-nodule specific features, wherein greater than 50% of the top 3 extracted features with the highest feature importance values are non-nodule specific features,
wherein lung parenchyma features comprise one or more of percentage of low attenuation area of the lung, percentage of high attenuation area of the lung, ratio of low attenuation or high attenuation area in an upper lung zone in comparison to a lower lung zone, percentage(s) of lung occupied by any of normal tissue, centrilobular emphysema, centrilobular nodule, ground glass, honeycombing, linear scar, nodular, reticular, subpleural line, other emphysema, or cyst, and
wherein body composition features comprise one or more of pectoralis cross-sectional area, pectoralis lean cross-sectional area, or sub-cutaneous fat cross-sectional area.
3. The method of claim 1, wherein the lung parenchyma features comprise one or more of densitometric measures of the lung parenchyma or local histogram measures of the lung parenchyma.
4. The method of claim 3, wherein the densitometric measures of the lung parenchyma comprise one or more of: percentage of low attenuation area of the lung, percentage

of high attenuation area of the lung, and ratio of low attenuation or high attenuation area in an upper lung zone in comparison to a lower lung zone.

5. The method of claim 3, wherein the local histogram measures of the lung parenchyma comprise one or more percentage(s) of lung occupied by any of normal tissue, centrilobular emphysema, centrilobular nodule, ground glass, honeycombing, linear scar, nodular, reticular, subpleural line, other emphysema, or cyst.
6. The method of claim 1, wherein body composition features comprise one or more of pectoralis cross-sectional area, pectoralis lean cross-sectional area, or sub-cutaneous fat cross-sectional area.
7. The method of any one of claims 1 or 3-6, wherein the extracted features further comprise nodule specific features.
8. The method of claim 7, wherein the nodule specific features comprise one or more of nodule specific attenuation, nodule margin description, nodule size, nodule shape, nodule texture, nodule diameter, Lung-RADS score, or radiomic features.
9. The method of claim 8, wherein radiomic features comprise one or more of first order statistics, 3D shape based features, 2D shape based features, gray level cooccurrence matrix, gray level run length matrix, gray level size zone matrix, neighboring gray tone difference matrix, and gray level dependence matrix.
10. The method of any one of claims 7-9, wherein the nodule specific features are extracted from a radiologist report.
11. The method of any one of claims 7-9, wherein the nodule specific features are computationally extracted by implementing an image analysis algorithm.
12. The method of any one of claims 1 or 3-11, wherein predicting the one or more future risks of lung cancer for the subject comprises applying a 5 year risk prediction model to predict whether the subject is likely to develop lung cancer within 5 years.
13. The method of claim 12, wherein the 5 year risk prediction model comprises nodule specific features and non-nodule specific features, wherein the non-nodule specific features have higher feature importance values than the nodule specific features.
14. The method of claim 13, wherein greater than 50% of the top 3 extracted features with the highest feature importance values are non-nodule specific features.
15. The method of claim 13, wherein greater than 50% of the top 5 extracted features with the highest feature importance values are non-nodule specific features.
16. The method of claim 13, wherein greater than 50% of the top 10 extracted features with the highest feature importance values are non-nodule specific features.

17. The method of any one of claims 12-16, wherein determining that the subject is a candidate comprises obtaining a classification of the subject in one of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, Lung-RADS 4A, or Lung-RADS 4B.
18. The method of claim 17, wherein the 5 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.74.
19. The method of claim 17, wherein the 5 year risk prediction model achieves at least a 5.1-fold increase in cumulative incidence in comparison to a background rate.
20. The method of any one of claims 12-16, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, or Lung-RADS 4A.
21. The method of claim 20, wherein the 5 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.72.
22. The method of claim 20, wherein the 5 year risk prediction model achieves at least a 3.9-fold increase in cumulative incidence in comparison to a background rate.
23. The method of any one of claims 12-16, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, or Lung-RADS 3.
24. The method of claim 23, wherein the 5 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.67.
25. The method of claim 23, wherein the 5 year risk prediction model achieves at least a 3.7-fold increase in cumulative incidence in comparison to a background rate.
26. The method of any one of claims 12-16, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1 or Lung-RADS 2.
27. The method of claim 26, wherein the 5 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.65.
28. The method of claim 26, wherein the 5 year risk prediction model achieves at least a 1.9-fold increase in cumulative incidence in comparison to a background rate.
29. The method of any one of claims 12-16, wherein determining that the subject is a candidate further comprises determining that the subject is classified in Lung-RADS 1.
30. The method of claim 29, wherein the 5 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.57.

31. The method of claim 29, wherein the 5 year risk prediction model achieves at least a 1.9-fold increase in cumulative incidence in comparison to a background rate.
32. The method of any one of claims 1 or 3-11, wherein predicting the one or more future risks of lung cancer for the subject comprises applying a 3 year risk prediction model to predict whether the subject is likely to develop lung cancer within 3 years.
33. The method of claim 32, wherein the 3 year risk prediction model comprises nodule specific features and non-nodule specific features, wherein the non-nodule specific features have higher feature importance values than the nodule-specific features.
34. The method of claim 33, wherein greater than 50% of the top 5 extracted features with the highest feature importance values are non-nodule specific features.
35. The method of claim 33, wherein greater than 50% of the top 10 extracted features with the highest feature importance values are non-nodule specific features.
36. The method of any one of claims 32-35, wherein determining that the subject is a candidate comprises obtaining a classification of the subject in one of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, Lung-RADS 4A, or Lung-RADS 4B.
37. The method of claim 36, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.79.
38. The method of claim 36, wherein the 3 year risk prediction model achieves at least a 6.3-fold increase in cumulative incidence in comparison to a background rate.
39. The method of any one of claims 32-35, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, or Lung-RADS 4A.
40. The method of claim 39, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.72.
41. The method of claim 39, wherein the 3 year risk prediction model achieves at least a 5.1-fold increase in cumulative incidence in comparison to a background rate.
42. The method of any one of claims 32-35, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, or Lung-RADS 3.
43. The method of claim 42, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.72.
44. The method of claim 42, wherein the 3 year risk prediction model achieves at least a 5.7-fold increase in cumulative incidence in comparison to a background rate.

45. The method of claim 42, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.676.
46. The method of any one of claims 32-35, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1 or Lung-RADS 2.
47. The method of claim 46, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.65.
48. The method of claim 46, wherein the 3 year risk prediction model achieves at least a 3-fold increase in cumulative incidence in comparison to a background rate.
49. The method of any one of claims 32-35, wherein determining that the subject is a candidate further comprises determining that the subject is classified in Lung-RADS 1.
50. The method of claim 49, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.60.
51. The method of claim 49, wherein the 3 year risk prediction model achieves at least a 2.3-fold increase in cumulative incidence in comparison to a background rate.
52. The method of any one of claims 1 or 3-11, wherein predicting the one or more future risks of lung cancer for the subject comprises applying a 1 year risk prediction model to predict whether the subject is likely to develop lung cancer within 1 year.
53. The method of claim 52, wherein the 1 year risk prediction model comprises nodule specific features and non-nodule specific features, wherein the non-nodule specific features have higher feature importance values than the nodule-specific features.
54. The method of any one of claims 52 or 53, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1 or Lung-RADS 2.
55. The method of claim 54, wherein the 1 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.72.
56. The method of claim 54, wherein the 1 year risk prediction model achieves at least a 5.5-fold increase in cumulative incidence in comparison to a background rate.
57. The method of any one of claims 52 or 53, wherein determining that the subject is a candidate further comprises determining that the subject is classified in Lung-RADS 1.
58. The method of claim 57, wherein the 1 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.57.

59. The method of claim 52, wherein the 1 year risk prediction model comprises nodule specific features and non-nodule specific features, wherein the nodule specific features have higher feature importance values than the non-nodule specific features.
60. The method of claim 59, wherein greater than 50% of the top 3 extracted features with the highest feature importance values are nodule specific features.
61. The method of any one of claims 59-60, wherein determining that the subject is a candidate comprises obtaining a classification of the subject in one of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, Lung-RADS 4A, or Lung-RADS 4B.
62. The method of claim 61, wherein the 1 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.90.
63. The method of claim 61, wherein the 1 year risk prediction model achieves at least a 11-fold increase in cumulative incidence in comparison to a background rate.
64. The method of any one of claims 59-60, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, or Lung-RADS 4A.
65. The method of claim 64, wherein the 1 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.81.
66. The method of claim 64, wherein the 1 year risk prediction model achieves at least a 7.6-fold increase in cumulative incidence in comparison to a background rate.
67. The method of any one of claims 60-65, wherein greater than 50% of the top 5 extracted features with the highest feature importance values are nodule specific features.
68. The method of any one of claims 59-60, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, or Lung-RADS 3.
69. The method of claim 68, wherein the 1 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.82.
70. The method of claim 64, wherein the 1 year risk prediction model achieves at least a 8.6-fold increase in cumulative incidence in comparison to a background rate.
71. The method of any one of claims 1 or 3-11, wherein predicting the one or more future risks of lung cancer for the subject comprises applying multiple risk prediction models to predict whether the subject is likely to develop lung cancer within N different time periods.

72. The method of claim 71, wherein at least one of the N different time periods is any one of 6 months, 1 year, 1.5 years, 2 years, 2.5 years, 3 years, 3.5 years, 4 years, 4.5 years, 5 years, 5.5 years, 6 years, 6.5 years, 7 years, 7.5 years, 8 years, 8.5 years, 9 years, 9.5 years, 10 years, 10.5 years, 11 years, 11.5 years, 12 years, 12.5 years, 13 years, 13.5 years, 14 years, 14.5 years, 15 years, 15.5 years, 16 years, 16.5 years, 17 years, 17.5 years, 18 years, 18.5 years, 19 years, 19.5 years, or 20 years.
73. The method of claim 71, wherein N is 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, or 20 different time periods.
74. The method of any one of claims 1-73, wherein one of the one or more risk prediction models is a Lung-RADS 1-4B prediction model that is trained to predict the future risk of lung cancer using training images captured from a training cohort of training individuals classified in any of Lung-RADS 1-4B.
75. The method of any one of claims 1-73, wherein one of the one or more risk prediction models is a Lung-RADS 1-4A model trained to predict the future risk of lung cancer using training images captured from a training cohort of training individuals classified in any of Lung-RADS 1-4A.
76. The method of any one of claims 1-73, wherein one of the one or more risk prediction models is a Lung-RADS 1-3 model to predict the future risk of lung cancer using training images captured from a training cohort of training individuals classified in any of Lung-RADS 1-3.
77. The method of any one of claims 1-73, wherein one of the one or more risk prediction models is a Lung-RADS 1-2 model trained to predict the future risk of lung cancer using training images captured from a training cohort of training individuals classified in either Lung-RADS 1 or 2.
78. The method of any one of claims 1-73, wherein one of the one or more risk prediction models is a Lung-RADS 1 model trained to predict the future risk of lung cancer using training images captured from a training cohort of training individuals classified in Lung-RADS 1.
79. The method of any one of claims 74-78, wherein a majority of training individuals in the training cohort are previously classified in Lung-RADS 1.
80. The method of any one of claims 1-80, wherein the one or more images are computed tomography (CT) images or X-ray images.
81. The method of any one of claims 1-80, wherein the one or more images comprises are thoracic CT images or chest X-ray images.

82. The method of any one of claims 1-81, wherein the risk prediction model is trained using training images of the National Lung Screening Trial (NLST).
83. The method of any one of claims 1-82, further comprising:
 - prior to predicting one or more future risks of lung cancer for the subject:
 - obtaining nodule-specific features corresponding to the subject;
 - determining that the subject is a candidate for future risk prediction based on the nodule-specific features.
84. The method of claim 83, wherein determining that the subject is a candidate comprises determining that the subject does not have lung cancer or is at low-risk of developing lung cancer.
85. The method of claim 84, wherein determining that the subject is at low-risk of developing lung cancer comprises determining that the subject does not have a nodule based on the nodule-specific features.
86. The method of any one of claims 1-85, wherein the lung cancer is either non-small cell lung cancer or small cell lung cancer.
87. The method of any one of claims 1-85, wherein the lung cancer is either adenocarcinoma or squamous cell carcinoma.
88. The method of any one of claims 1-87, further comprising selecting a clinical response for the subject based on the predicted future risk of lung cancer.
89. The method of claim 88, wherein selecting a clinical response for the subject comprises selecting an intervention for treating the subject.
90. The method of claim 89, wherein selecting an intervention comprises selecting a therapeutic for administration to the subject.
91. The method of claim 90, wherein the selected therapeutic is prophylactically administered to the subject to delay or prevent the development of the lung cancer.
92. The method of claim 88, wherein the clinical response comprises providing counseling to the subject to modify behavior of the subject.
93. The method of claim 88, wherein the clinical response comprises increasing a frequency of follow up for the subject.
94. The method of claim 88, wherein the clinical response comprises performing or scheduling to be performed an additional risk prediction test to confirm the predicted future risk of lung cancer.
95. The method of any one of claims 1-94, wherein one or more of the trained risk prediction models are one of a random forest model or gradient boosted model.

96. A non-transitory computer readable medium for predicting one or more future risks of lung cancer for a subject, the non-transitory computer readable medium comprising instructions that, when executed by a processor, cause the processor to:
- obtain one or more images captured from the subject at a single timepoint;
 - extract features from the one or more obtained images, the extracted features comprising at least non-nodule specific features, wherein the non-nodule specific features comprise one or both of lung parenchyma features or body composition features;
 - predict one or more future risks of lung cancer for the subject by applying one or more trained risk prediction models to analyze the extracted features from the one or more obtained images.
97. The non-transitory computer readable medium of claim 96, wherein the instructions that cause the processor to predict the one or more future risks of lung cancer for the subject further comprises instructions that, when executed by the processor, cause the processor to apply a M year risk prediction model to predict whether the subject is likely to develop lung cancer within M years, wherein the M year risk prediction model comprises nodule specific features and non-nodule specific features, wherein greater than 50% of the top 3 extracted features with the highest feature importance values are non-nodule specific features,
- wherein lung parenchyma features comprise one or more of percentage of low attenuation area of the lung, percentage of high attenuation area of the lung, ratio of low attenuation or high attenuation area in an upper lung zone in comparison to a lower lung zone, percentage(s) of lung occupied by any of normal tissue, centrilobular emphysema, centrilobular nodule, ground glass, honeycombing, linear scar, nodular, reticular, subpleural line, other emphysema, or cyst, and
 - wherein body composition features comprise one or more of pectoralis cross-sectional area, pectoralis lean cross-sectional area, or sub-cutaneous fat cross-sectional area.
98. The non-transitory computer readable medium of claim 96, wherein the lung parenchyma features comprise one or more of densitometric measures of the lung parenchyma or local histogram measures of the lung parenchyma.
99. The non-transitory computer readable medium of claim 98, wherein the densitometric measures of the lung parenchyma comprise one or more of: percentage of low

attenuation area of the lung, percentage of high attenuation area of the lung, and ratio of low attenuation or high attenuation area in an upper lung zone in comparison to a lower lung zone.

100. The non-transitory computer readable medium of claim 98, wherein the local histogram measures of the lung parenchyma comprise one or more percentage(s) of lung occupied by any of normal tissue, centrilobular emphysema, centrilobular nodule, ground glass, honeycombing, linear scar, nodular, reticular, subpleural line, other emphysema, or cyst.
101. The non-transitory computer readable medium of claim 96, wherein body composition features comprise one or more of pectoralis cross-sectional area, pectoralis lean cross-sectional area, or sub-cutaneous fat cross-sectional area.
102. The non-transitory computer readable medium of any one of claims 96 or 98-101, wherein the extracted features further comprise nodule specific features.
103. The non-transitory computer readable medium of claim 102, wherein the nodule specific features comprise one or more of nodule specific attenuation, nodule margin description, nodule size, nodule shape, nodule texture, nodule diameter, Lung-RADS score, or radiomic features.
104. The non-transitory computer readable medium of claim 103, wherein radiomic features comprise one or more of first order statistics, 3D shape based features, 2D shape based features, Gray level cooccurrence matrix, gray level run length matrix, gray level size zone matrix, neighboring gray tone difference matrix, and gray level dependence matrix.
105. The non-transitory computer readable medium of any one of claims 102-104, wherein the nodule specific features are extracted from a radiologist report.
106. The non-transitory computer readable medium of any one of claims 102-104, wherein the nodule specific features are computationally extracted by implementing an image analysis algorithm.
107. The non-transitory computer readable medium of any one of claims 96 or 98-106, wherein the instructions that cause the processor to predict the one or more future risks of lung cancer for the subject further comprises instructions that, when executed by the processor, cause the processor to apply a 5 year risk prediction model to predict whether the subject is likely to develop lung cancer within 5 years.
108. The non-transitory computer readable medium of claim 107, wherein the 5 year risk prediction model comprises nodule specific features and non-nodule specific

features, wherein the non-nodule specific features have higher feature importance values than the nodule specific features.

109. The non-transitory computer readable medium of claim 108, wherein greater than 50% of the top 3 extracted features with the highest feature importance values are non-nodule specific features.
110. The non-transitory computer readable medium of claim 108, wherein greater than 50% of the top 5 extracted features with the highest feature importance values are non-nodule specific features.
111. The non-transitory computer readable medium of claim 108, wherein greater than 50% of the top 10 extracted features with the highest feature importance values are non-nodule specific features.
112. The non-transitory computer readable medium of any one of claims 107-111, wherein determining that the subject is a candidate comprises obtaining a classification of the subject in one of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, Lung-RADS 4A, or Lung-RADS 4B.
113. The non-transitory computer readable medium of claim 112, wherein the 5 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.74.
114. The non-transitory computer readable medium of claim 112, wherein the 5 year risk prediction model achieves at least a 5.1-fold increase in cumulative incidence in comparison to a background rate.
115. The non-transitory computer readable medium of any one of claims 107-111, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, or Lung-RADS 4A.
116. The non-transitory computer readable medium of claim 115, wherein the 5 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.72.
117. The non-transitory computer readable medium of claim 115, wherein the 5 year risk prediction model achieves at least a 3.9-fold increase in cumulative incidence in comparison to a background rate.
118. The non-transitory computer readable medium of any one of claims 107-111, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, or Lung-RADS 3.
119. The non-transitory computer readable medium of claim 118, wherein the 5 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.67.

120. The non-transitory computer readable medium of claim 118, wherein the 5 year risk prediction model achieves at least a 3.7-fold increase in cumulative incidence in comparison to a background rate.
121. The non-transitory computer readable medium of any one of claims 107-111, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1 or Lung-RADS 2.
122. The non-transitory computer readable medium of claim 121, wherein the 5 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.65.
123. The non-transitory computer readable medium of claim 121, wherein the 5 year risk prediction model achieves at least a 1.9-fold increase in cumulative incidence in comparison to a background rate.
124. The non-transitory computer readable medium of any one of claims 107-111, wherein determining that the subject is a candidate further comprises determining that the subject is classified in Lung-RADS 1.
125. The non-transitory computer readable medium of claim 124, wherein the 5 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.57.
126. The non-transitory computer readable medium of claim 124, wherein the 5 year risk prediction model achieves at least a 1.9-fold increase in cumulative incidence in comparison to a background rate.
127. The non-transitory computer readable medium of any one of claims 96 or 98-106, wherein the instructions that cause the processor to predict the one or more future risks of lung cancer for the subject further comprises instructions that, when executed by the processor, cause the processor to apply a 3 year risk prediction model to predict whether the subject is likely to develop lung cancer within 3 years.
128. The non-transitory computer readable medium of claim 127, wherein the 3 year risk prediction model comprises nodule specific features and non-nodule specific features, wherein the non-nodule specific features have higher feature importance values than the nodule-specific features.
129. The non-transitory computer readable medium of claim 128, wherein greater than 50% of the top 5 extracted features with the highest feature importance values are non-nodule specific features.
130. The non-transitory computer readable medium of claim 128, wherein greater than 50% of the top 10 extracted features with the highest feature importance values are non-nodule specific features.

131. The non-transitory computer readable medium of claim 127-130, wherein determining that the subject is a candidate comprises obtaining a classification of the subject in one of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, Lung-RADS 4A, or Lung-RADS 4B.
132. The non-transitory computer readable medium of claim 131, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.79.
133. The non-transitory computer readable medium of claim 131, wherein the 3 year risk prediction model achieves at least a 6.3-fold increase in cumulative incidence in comparison to a background rate.
134. The non-transitory computer readable medium of claim 127-130, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, or Lung-RADS 4A.
135. The non-transitory computer readable medium of claim 134, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.72.
136. The non-transitory computer readable medium of claim 134, wherein the 3 year risk prediction model achieves at least a 5.1-fold increase in cumulative incidence in comparison to a background rate.
137. The non-transitory computer readable medium of claim 127-130, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, or Lung-RADS 3.
138. The non-transitory computer readable medium of claim 137, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.72.
139. The non-transitory computer readable medium of claim 137, wherein the 3 year risk prediction model achieves at least a 5.7-fold increase in cumulative incidence in comparison to a background rate.
140. The non-transitory computer readable medium of claim 137, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.676.
141. The non-transitory computer readable medium of claim 127-130, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1 or Lung-RADS 2.
142. The non-transitory computer readable medium of claim 141, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.65.

143. The non-transitory computer readable medium of claim 141, wherein the 3 year risk prediction model achieves at least a 3-fold increase in cumulative incidence in comparison to a background rate.
144. The non-transitory computer readable medium of claim 127-130, wherein determining that the subject is a candidate further comprises determining that the subject is classified in Lung-RADS 1.
145. The non-transitory computer readable medium of claim 144, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.60.
146. The non-transitory computer readable medium of claim 144, wherein the 3 year risk prediction model achieves at least a 2.3-fold increase in cumulative incidence in comparison to a background rate.
147. The non-transitory computer readable medium of any one of claims 96 or 98-106, wherein the instructions that cause the processor to predict the one or more future risks of lung cancer for the subject further comprises instructions that, when executed by the processor, cause the processor to apply a 1 year risk prediction model to predict whether the subject is likely to develop lung cancer within 1 year.
148. The non-transitory computer readable medium of claim 147, wherein the 1 year risk prediction model comprises nodule specific features and non-nodule specific features, wherein the non-nodule specific features have higher feature importance values than the nodule-specific features.
149. The non-transitory computer readable medium of any one of claims 147 or 148, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1 or Lung-RADS 2.
150. The non-transitory computer readable medium of claim 149, wherein the 1 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.72.
151. The non-transitory computer readable medium of claim 149, wherein the 1 year risk prediction model achieves at least a 5.5-fold increase in cumulative incidence in comparison to a background rate.
152. The non-transitory computer readable medium of any one of claims 147 or 148, wherein determining that the subject is a candidate further comprises determining that the subject is classified in Lung-RADS 1.
153. The non-transitory computer readable medium of claim 152, wherein the 1 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.57.

154. The non-transitory computer readable medium of claim 147, wherein the 1 year risk prediction model comprises nodule specific features and non-nodule specific features, wherein the nodule specific features have higher feature importance values than the non-nodule specific features.
155. The non-transitory computer readable medium of claim 154, wherein greater than 50% of the top 3 extracted features with the highest feature importance values are non-nodule specific features.
156. The non-transitory computer readable medium of any one of claims 154-155, wherein determining that the subject is a candidate comprises obtaining a classification of the subject in one of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, Lung-RADS 4A, or Lung-RADS 4B.
157. The non-transitory computer readable medium of claim 156, wherein the 1 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.90.
158. The non-transitory computer readable medium of claim 156, wherein the 1 year risk prediction model achieves at least a 11-fold increase in cumulative incidence in comparison to a background rate.
159. The non-transitory computer readable medium of any one of claims 154-155, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, or Lung-RADS 4A.
160. The non-transitory computer readable medium of claim 159, wherein the 1 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.81.
161. The non-transitory computer readable medium of claim 159, wherein the 1 year risk prediction model achieves at least a 7.6-fold increase in cumulative incidence in comparison to a background rate.
162. The non-transitory computer readable medium of any one of claims 155-160, wherein greater than 50% of the top 5 extracted features with the highest feature importance values are non-nodule specific features.
163. The non-transitory computer readable medium of any one of claims 154-155, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, or Lung-RADS 3.
164. The non-transitory computer readable medium of claim 162, wherein the 1 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.82.

165. The non-transitory computer readable medium of claim 162, wherein the 1 year risk prediction model achieves at least a 8.6-fold increase in cumulative incidence in comparison to a background rate.
166. The non-transitory computer readable medium of any one of claims 96 or 98-106, wherein the instructions that cause the processor to predict the one or more future risks of lung cancer for the subject further comprises instructions that, when executed by the processor, cause the processor to apply multiple risk prediction models to predict whether the subject is likely to develop lung cancer within N different time periods.
167. The non-transitory computer readable medium of claim 166, wherein at least one of the N different time periods is any one of 6 months, 1 year, 1.5 years, 2 years, 2.5 years, 3 years, 3.5 years, 4 years, 4.5 years, 5 years, 5.5 years, 6 years, 6.5 years, 7 years, 7.5 years, 8 years, 8.5 years, 9 years, 9.5 years, 10 years, 10.5 years, 11 years, 11.5 years, 12 years, 12.5 years, 13 years, 13.5 years, 14 years, 14.5 years, 15 years, 15.5 years, 16 years, 16.5 years, 17 years, 17.5 years, 18 years, 18.5 years, 19 years, 19.5 years, or 20 years.
168. The non-transitory computer readable medium of claim 166, wherein N is 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, or 20 different time periods.
169. The non-transitory computer readable medium of any one of claims 96-166, wherein one of the one or more risk prediction models is a Lung-RADS 1-4B prediction model that is trained to predict the future risk of lung cancer using training images captured from a training cohort of training individuals classified in any of Lung-RADS 1-4B.
170. The non-transitory computer readable medium of any one of claims 96-166, wherein one of the one or more risk prediction models is a Lung-RADS 1-4A model trained to predict the future risk of lung cancer using training images captured from a training cohort of training individuals classified in any of Lung-RADS 1-4A.
171. The non-transitory computer readable medium of any one of claims 96-166, wherein one of the one or more risk prediction models is a Lung-RADS 1-3 model to predict the future risk of lung cancer using training images captured from a training cohort of training individuals classified in any of Lung-RADS 1-3.
172. The non-transitory computer readable medium of any one of claims 96-166, wherein one of the one or more risk prediction models is a Lung-RADS 1-2 model

- trained to predict the future risk of lung cancer using training images captured from a training cohort of training individuals classified in either Lung-RADS 1 or 2.
173. The non-transitory computer readable medium of any one of claims 96-166, wherein one of the one or more risk prediction models is a Lung-RADS 1 model trained to predict the future risk of lung cancer using training images captured from a training cohort of training individuals classified in Lung-RADS 1.
174. The non-transitory computer readable medium of any one of claims 169-173, wherein a majority of training individuals in the training cohort are previously classified in Lung-RADS 1.
175. The non-transitory computer readable medium of any one of claims 96-174, wherein the one or more images are computed tomography (CT) images or X-ray images.
176. The non-transitory computer readable medium of any one of claims 96-175, wherein the one or more images comprises are thoracic CT images or chest X-ray images.
177. The non-transitory computer readable medium of any one of claims 96-176, wherein the risk prediction model is trained using training images of the National Lung Screening Trial (NLST).
178. The non-transitory computer readable medium of any one of claims 96-177, further comprising instructions that, when executed by the processor, cause the processor to: prior to predicting one or more future risks of lung cancer for the subject:
- obtain nodule-specific features corresponding to the subject;
 - determine that the subject is a candidate for future risk prediction based on the nodule-specific features.
179. The non-transitory computer readable medium of claim 178, wherein the instructions that cause the processor to determine that the subject is a candidate further comprises instructions that, when executed by the processor, cause the processor to determine that the subject does not have lung cancer or is at low-risk of developing lung cancer.
180. The non-transitory computer readable medium of claim 179, wherein the instructions that cause the processor to determine that the subject is at low-risk of developing lung cancer further comprises instructions that, when executed by the processor, cause the processor to determine that the subject does not have a nodule based on the nodule-specific features.

181. The non-transitory computer readable medium of any one of claims 96-180, wherein the lung cancer is either non-small cell lung cancer or small cell lung cancer.
182. The non-transitory computer readable medium of any one of claims 96-180, wherein the lung cancer is either adenocarcinoma or squamous cell carcinoma.
183. The non-transitory computer readable medium of any one of claims 96-182, further comprising instructions that, when executed by the processor, cause the processor to select an intervention for treating the subject based on the predicted future risk of lung cancer.
184. The non-transitory computer readable medium of claim 183, wherein the instructions that cause the processor to select an intervention further comprises instructions that, when executed by the processor, cause the processor to select a therapeutic for administration to the subject.
185. The non-transitory computer readable medium of claim 184, wherein the selected therapeutic is a prophylactic for delaying or preventing the development of the lung cancer.
186. The non-transitory computer readable medium of any one of claims 96-185, wherein one or more of the trained risk prediction models are one of a random forest model or gradient boosted model.
187. A system for predicting one or more future risks of lung cancer for a subject, the system comprising:
an imaging device configured to capture one or more images of the subject at a single timepoint; and
a computing device configured to perform the steps of:
obtaining one or more images captured from the subject at the single timepoint;
extracting features from the one or more obtained images, the extracted features comprising at least non-nodule specific features, wherein the non-nodule specific features comprise one or both of lung parenchyma features or body composition features;
predicting one or more future risks of lung cancer for the subject by applying one or more trained risk prediction models to analyze the extracted features from the one or more obtained images.
188. The system of claim 187, wherein predicting the one or more future risks of lung cancer for the subject comprises applying a M year risk prediction model to

predict whether the subject is likely to develop lung cancer within M years, wherein the M year risk prediction model comprises nodule specific features and non-nodule specific features, wherein greater than 50% of the top 3 extracted features with the highest feature importance values are non-nodule specific features,

wherein lung parenchyma features comprise one or more of percentage of low

attenuation area of the lung, percentage of high attenuation area of the lung, ratio of low attenuation or high attenuation area in an upper lung zone in comparison to a lower lung zone, percentage(s) of lung occupied by any of normal tissue, centrilobular emphysema, centrilobular nodule, ground glass, honeycombing, linear scar, nodular, reticular, subpleural line, other emphysema, or cyst, and

wherein body composition features comprise one or more of pectoralis cross-sectional area, pectoralis lean cross-sectional area, or sub-cutaneous fat cross-sectional area.

189. The system of claim 187, wherein the lung parenchyma features comprise one or more of densitometric measures of the lung parenchyma or local histogram measures of the lung parenchyma.
190. The system of claim 189, wherein the densitometric measures of the lung parenchyma comprise one or more of: percentage of low attenuation area of the lung, percentage of high attenuation area of the lung, and ratio of low attenuation or high attenuation area in an upper lung zone in comparison to a lower lung zone.
191. The system of claim 189, wherein the local histogram measures of the lung parenchyma comprise one or more percentage(s) of lung occupied by any of normal tissue, centrilobular emphysema, centrilobular nodule, ground glass, honeycombing, linear scar, nodular, reticular, subpleural line, other emphysema, or cyst.
192. The system of claim 187, wherein body composition features comprise one or more of pectoralis cross-sectional area, pectoralis lean cross-sectional area, or sub-cutaneous fat cross-sectional area.
193. The system of any one of claims 187 or 189-192, wherein the extracted features further comprise nodule specific features.
194. The system of claim 193, wherein the nodule specific features comprise one or more of nodule specific attenuation, nodule margin description, nodule size, nodule shape, nodule texture, nodule diameter, Lung-RADS score, or radiomic features.

195. The system of claim 194, wherein radiomic features comprise one or more of first order statistics, 3D shape based features, 2D shape based features, Gray level cooccurrence matrix, gray level run length matrix, gray level size zone matrix, neighboring gray tone difference matrix, and gray level dependence matrix.
196. The system of any one of claims 193-195, wherein the nodule specific features are extracted from a radiologist report.
197. The system of any one of claims 193-195, wherein the nodule specific features are computationally extracted by implementing an image analysis algorithm.
198. The system of any one of claims 187 or 189-197, wherein predicting the one or more future risks of lung cancer for the subject comprises applying a 5 year risk prediction model to predict whether the subject is likely to develop lung cancer within 5 years.
199. The system of claim 198, wherein the 5 year risk prediction model comprises nodule specific features and non-nodule specific features, wherein the non-nodule specific features have higher feature importance values than the nodule specific features.
200. The system of claim 199, wherein greater than 50% of the top 3 extracted features with the highest feature importance values are non-nodule specific features.
201. The system of claim 199, wherein greater than 50% of the top 5 extracted features with the highest feature importance values are non-nodule specific features.
202. The system of claim 199, wherein greater than 50% of the top 10 extracted features with the highest feature importance values are non-nodule specific features.
203. The system of any one of claims 198-202, wherein determining that the subject is a candidate comprises obtaining a classification of the subject in one of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, Lung-RADS 4A, or Lung-RADS 4B.
204. The system of claim 203, wherein the 5 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.74.
205. The system of claim 203, wherein the 5 year risk prediction model achieves at least a 5.1-fold increase in cumulative incidence in comparison to a background rate.
206. The system of any one of claims 198-202, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, or Lung-RADS 4A.
207. The system of claim 206, wherein the 5 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.72.

208. The system of claim 206, wherein the 5 year risk prediction model achieves at least a 3.9-fold increase in cumulative incidence in comparison to a background rate.
209. The system of any one of claims 198-202, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, or Lung-RADS 3.
210. The system of claim 209, wherein the 5 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.67.
211. The system of claim 209, wherein the 5 year risk prediction model achieves at least a 3.7-fold increase in cumulative incidence in comparison to a background rate.
212. The system of any one of claims 198-202, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1 or Lung-RADS 2.
213. The system of claim 212, wherein the 5 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.65.
214. The system of claim 212, wherein the 5 year risk prediction model achieves at least a 1.9-fold increase in cumulative incidence in comparison to a background rate.
215. The system of any one of claims 198-202, wherein determining that the subject is a candidate further comprises determining that the subject is classified in Lung-RADS 1.
216. The system of claim 215, wherein the 5 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.57.
217. The system of claim 215, wherein the 5 year risk prediction model achieves at least a 1.9-fold increase in cumulative incidence in comparison to a background rate.
218. The system of any one of claims 187 or 189-197, wherein predicting the one or more future risks of lung cancer for the subject comprises applying a 3 year risk prediction model to predict whether the subject is likely to develop lung cancer within 3 years.
219. The system of claim 218, wherein the 3 year risk prediction model comprises nodule specific features and non-nodule specific features, wherein the non-nodule specific features have higher feature importance values than the nodule-specific features.
220. The system of claim 219, wherein greater than 50% of the top 5 extracted features with the highest feature importance values are non-nodule specific features.

221. The system of claim 219, wherein greater than 50% of the top 10 extracted features with the highest feature importance values are non-nodule specific features.
222. The system of claim 218-221, wherein determining that the subject is a candidate comprises obtaining a classification of the subject in one of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, Lung-RADS 4A, or Lung-RADS 4B.
223. The system of claim 222, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.79.
224. The system of claim 222, wherein the 3 year risk prediction model achieves at least a 6.3-fold increase in cumulative incidence in comparison to a background rate.
225. The system of claim 218-221, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, or Lung-RADS 4A.
226. The system of claim 225, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.72.
227. The system of claim 225, wherein the 3 year risk prediction model achieves at least a 5.1-fold increase in cumulative incidence in comparison to a background rate.
228. The system of claim 218-221, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, or Lung-RADS 3.
229. The system of claim 228, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.72.
230. The system of claim 228, wherein the 3 year risk prediction model achieves at least a 5.7-fold increase in cumulative incidence in comparison to a background rate.
231. The system of claim 228, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.676.
232. The system of claim 218-221, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1 or Lung-RADS 2.
233. The system of claim 232, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.65.
234. The system of claim 232, wherein the 3 year risk prediction model achieves at least a 3-fold increase in cumulative incidence in comparison to a background rate.
235. The system of claim 218-221, wherein determining that the subject is a candidate further comprises determining that the subject is classified in Lung-RADS 1.

236. The system of claim 235, wherein the 3 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.60.
237. The system of claim 235, wherein the 3 year risk prediction model achieves at least a 2.3-fold increase in cumulative incidence in comparison to a background rate.
238. The system of any one of claims 187 or 189-197, wherein predicting the one or more future risks of lung cancer for the subject comprises applying a 1 year risk prediction model to predict whether the subject is likely to develop lung cancer within 1 year.
239. The system of claim 238, wherein the 1 year risk prediction model comprises nodule specific features and non-nodule specific features, wherein the non-nodule specific features have higher feature importance values than the nodule-specific features.
240. The system of any one of claims 238 or 239, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1 or Lung-RADS 2.
241. The system of claim 240, wherein the 1 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.72.
242. The system of claim 240, wherein the 1 year risk prediction model achieves at least a 5.5-fold increase in cumulative incidence in comparison to a background rate.
243. The system of any one of claims 238 or 239, wherein determining that the subject is a candidate further comprises determining that the subject is classified in Lung-RADS 1.
244. The system of claim 243, wherein the 1 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.57.
245. The system of claim 238, wherein the 1 year risk prediction model comprises nodule specific features and non-nodule specific features, wherein the nodule specific features have higher feature importance values than the non-nodule specific features.
246. The system of claim 245, wherein greater than 50% of the top 3 extracted features with the highest feature importance values are non-nodule specific features.
247. The system of any one of claims 245-246, wherein determining that the subject is a candidate comprises obtaining a classification of the subject in one of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, Lung-RADS 4A, or Lung-RADS 4B.
248. The system of claim 247, wherein the 1 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.90.

249. The system of claim 247, wherein the 1 year risk prediction model achieves at least a 11-fold increase in cumulative incidence in comparison to a background rate.
250. The system of any one of claims 245-246, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, Lung-RADS 3, or Lung-RADS 4A.
251. The system of claim 250, wherein the 1 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.81.
252. The system of claim 250, wherein the 1 year risk prediction model achieves at least a 7.6-fold increase in cumulative incidence in comparison to a background rate.
253. The system of any one of claims 246-251, wherein greater than 50% of the top 5 extracted features with the highest feature importance values are non-nodule specific features.
254. The system of any one of claims 245-246, wherein determining that the subject is a candidate further comprises determining that the subject is classified in any of Lung-RADS 1, Lung-RADS 2, or Lung-RADS 3.
255. The system of claim 254, wherein the 1 year risk prediction model exhibits an area under the curve (AUC) value of at least 0.82.
256. The system of claim 254, wherein the 1 year risk prediction model achieves at least a 8.6-fold increase in cumulative incidence in comparison to a background rate.
257. The system of any one of claims 187 or 189-197, wherein predicting the one or more future risks of lung cancer for the subject comprises applying multiple risk prediction models to predict whether the subject is likely to develop lung cancer within N different time periods.
258. The system of claim 257, wherein at least one of the N different time periods is any one of 6 months, 1 year, 1.5 years, 2 years, 2.5 years, 3 years, 3.5 years, 4 years, 4.5 years, 5 years, 5.5 years, 6 years, 6.5 years, 7 years, 7.5 years, 8 years, 8.5 years, 9 years, 9.5 years, 10 years, 10.5 years, 11 years, 11.5 years, 12 years, 12.5 years, 13 years, 13.5 years, 14 years, 14.5 years, 15 years, 15.5 years, 16 years, 16.5 years, 17 years, 17.5 years, 18 years, 18.5 years, 19 years, 19.5 years, or 20 years.
259. The system of claim 257, wherein N is 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, or 20 different time periods.
260. The system of any one of claims 187-259, wherein one of the one or more risk prediction models is a Lung-RADS 1-4B prediction model that is trained to predict

the future risk of lung cancer using training images captured from a training cohort of training individuals classified in any of Lung-RADS 1-4B.

261. The system of any one of claims 187-259, wherein one of the one or more risk prediction models is a Lung-RADS 1-4A model trained to predict the future risk of lung cancer using training images captured from a training cohort of training individuals classified in any of Lung-RADS 1-4A.
262. The system of any one of claims 187-259, wherein one of the one or more risk prediction models is a Lung-RADS 1-3 model to predict the future risk of lung cancer using training images captured from a training cohort of training individuals classified in any of Lung-RADS 1-3.
263. The system of any one of claims 187-259, wherein one of the one or more risk prediction models is a Lung-RADS 1-2 model trained to predict the future risk of lung cancer using training images captured from a training cohort of training individuals classified in either Lung-RADS 1 or 2.
264. The system of any one of claims 187-259, wherein one of the one or more risk prediction models is a Lung-RADS 1 model trained to predict the future risk of lung cancer using training images captured from a training cohort of training individuals classified in Lung-RADS 1.
265. The system of any one of claims 260-264, wherein a majority of training individuals in the training cohort are previously classified in Lung-RADS 1.
266. The system of any one of claims 187-265, wherein the one or more images are computed tomography (CT) images or X-ray images.
267. The system of any one of claims 187-266, wherein the one or more images comprises are thoracic CT images or chest X-ray images.
268. The system of any one of claims 187-267, wherein the risk prediction model is trained using training images of the National Lung Screening Trial (NLST).
269. The system of any one of claims 187-268, wherein the computational device is further configured to:
 - prior to predicting one or more future risks of lung cancer for the subject:
 - obtaining nodule-specific features corresponding to the subject;
 - determining that the subject is a candidate for future risk prediction based on the nodule-specific features.

270. The system of claim 269, wherein determining that the subject is a candidate comprises determining that the subject does not have lung cancer or is at low-risk of developing lung cancer.
271. The system of claim 270, wherein determining that the subject is at low-risk of developing lung cancer comprises determining that the subject does not have a nodule based on the nodule-specific features.
272. The system of any one of claims 187-271, wherein the lung cancer is either non-small cell lung cancer or small cell lung cancer.
273. The system of any one of claims 187-271, wherein the lung cancer is either adenocarcinoma or squamous cell carcinoma.
274. The system of any one of claims 187-273, wherein the computing device is further configured to perform the step of selecting an intervention for treating the subject based on the predicted future risk of lung cancer.
275. The system of claim 274, wherein selecting an intervention for treating the subject comprises selecting a therapeutic for administration to the subject.
276. The system of claim 275, wherein the selected therapeutic is a prophylactic for delaying or preventing the development of the lung cancer.
277. The system of any one of claims 187-276, wherein one or more of the trained risk prediction models are one of a random forest model or gradient boosted model.