

# NSCLC Radiogenomics

# Summary

## Redirection Notice

This page will redirect to <https://www.cancerimagingarchive.net/collection/nsclc-radiogenomics/> in about 5 seconds.

Medical image biomarkers of cancer promise improvements in patient care through advances in precision medicine. Compared to genomic biomarkers, image biomarkers provide the advantages of being a non-invasive procedure, and characterizing a heterogeneous tumor in its entirety, as opposed to limited tissue available for biopsy. We developed a unique radiogenomic dataset from a Non-Small Cell Lung Cancer (NSCLC) cohort of 211 subjects. The dataset comprises Computed Tomography (CT), Positron Emission Tomography (PET)/CT images, semantic annotations of the tumors as observed on the medical images using a controlled vocabulary, segmentation maps of tumors in the CT scans, and quantitative values obtained from the PET/CT scans. Imaging data are also paired with gene mutation, RNA sequencing data from samples of surgically excised tumor tissue, and clinical data, including survival outcomes. This dataset was created to facilitate the discovery of the underlying relationship between genomic and medical image features, as well as the development and evaluation of prognostic medical image biomarkers.

Further details regarding this data-set may be found in Bakr, et. al, Sci Data. 2018 Oct 16;5:180202. doi: [10.1038/sdata.2018.202](https://doi.org/10.1038/sdata.2018.202), <https://www.ncbi.nlm.nih.gov/pubmed/30325352>.

For scientific and other inquiries about this dataset, please [contact TCIA's Helpdesk](#).

## Data Access

### Data Access

| Data Type                                 | Download all or Query/Filter                                                                                | License   |
|-------------------------------------------|-------------------------------------------------------------------------------------------------------------|-----------|
| Images and Segmentations (DICOM, 97.6 GB) | <a href="#">Download</a> <a href="#">Search</a><br>(Download requires <a href="#">NBIA Data Retriever</a> ) | CC BY 3.0 |
| AIM Annotations (XML, zip, 436 kB)        | <a href="#">Download</a>                                                                                    | CC BY 3.0 |
| Clinical Data (csv, 46 kB)                | <a href="#">Download</a>                                                                                    | CC BY 3.0 |

Click the Versions tab for more info about data releases.

## Additional Resources for this Dataset

The NCI Cancer Research Data Commons (CRDC) provides access to additional data and a cloud-based data science infrastructure that connects data sets with analytics tools to allow users to share, integrate, analyze, and visualize cancer research data.

- [Imaging Data Commons \(IDC\)](#) (Imaging Data)

The following external resources have been made available by the data submitters. These are not hosted or supported by TCIA, but may be useful to researchers utilizing this collection.

- [RNA sequence data](#) (Note: 130 subject subset)

## Third Party Analyses of this Dataset

TCIA encourages the community to [publish your analyses of our datasets](#). Below is a list of such third party analyses published using this Collection:

- [Crowds Cure Cancer: Data collected at the RSNA 2018 annual meeting \(Crowds-Cure-2018\)](#)
- [NSCLC Radiogenomics: Initial Stanford Study of 26 Cases \(NSCLC Radiogenomics-Stanford\)](#)

### Detailed Description

#### Detailed Description

| Collection Statistics  |             |
|------------------------|-------------|
| Modalities             | CT, PT, SEG |
| Number of Participants | 211         |
| Number of Studies      | 395         |
| Number of Series       | 1351        |
| Number of Images       | 286754      |
| Image Size (GB)        | 91.3        |

This collection was originally submitted to TCIA as a 26 subject pilot data set. You can learn more about that subset of the collection in the following [Analysis Results](#) publication:



#### Data Citation

Napel, Sandy, & Plevritis, Sylvia K. (2014). **NSCLC Radiogenomics: Initial Stanford Study of 26 Cases**. The Cancer Imaging Archive. <http://doi.org/10.7937/K9/TCIA.2014.X7ONY6B1>

### Citations & Data Usage Policy

#### Citations & Data Usage Policy

Users must abide by the [TCIA Data Usage Policy and Restrictions](#). Attribution should include references to the following citations:



#### Data Citation

Bakr, S., Gevaert, O., Echegaray, S., Ayers, K., Zhou, M., Shafiq, M., Zheng, H., Zhang, W., Leung, A., Kadoch, M., Shrager, J., Quon, A., Rubin, D., Plevritis, S., & Napel, S. (2017). **Data for NSCLC Radiogenomics (Version 4) [Data set]**. The Cancer Imaging Archive. <https://doi.org/10.7937/K9/TCIA.2017.7hs46erv>

### Publication Citation

Bakr, S., Gevaert, O., Echegaray, S., Ayers, K., Zhou, M., Shafiq, M., Zheng, H., Benson, J. A., Zhang, W., Leung, A., Kadoch, M., Hoang, C. D., Shrager, J., Quon, A., Rubin, D. L., Plevritis, S. K., & Napel, S. (2018). **A radiogenomic dataset of non-small cell lung cancer**. *Scientific data*, 5, 180202. <https://doi.org/10.1038/sdata.2018.202>

### Publication Citation

Gevaert, O., Xu, J., Hoang, C. D., Leung, A. N., Xu, Y., Quon, A., ... Plevritis, S. K. (2012, August). **Non-Small Cell Lung Cancer: Identifying Prognostic Imaging Biomarkers by Leveraging Public Gene Expression Microarray Data—Methods and Preliminary Results**. *Radiology*. Radiological Society of North America (RSNA). <http://doi.org/10.1148/radiol.12111607>

### TCIA Citation

Clark, K., Vendt, B., Smith, K., Freymann, J., Kirby, J., Koppel, P., Moore, S., Phillips, S., Maffitt, D., Pringle, M., Tarbox, L., & Prior, F. (2013). **The Cancer Imaging Archive (TCIA): Maintaining and Operating a Public Information Repository**. In *Journal of Digital Imaging* (Vol. 26, Issue 6, pp. 1045–1057). Springer Science and Business Media LLC. <https://doi.org/10.1007/s10278-013-9622-7> PMID: PMC3824915

## Other Publications Using This Data

TCIA maintains [a list of publications](#) that leverage TCIA data.

- Aonpong, P., Iwamoto, Y., Han, X. H., Lin, L., & Chen, Y. W. (2021). Improved Genotype-Guided Deep Radiomics Signatures for Recurrence Prediction of Non-Small Cell Lung Cancer *Annu Int Conf IEEE Eng Med Biol Soc*, 2021, 3561-3564. doi:<https://doi.org/10.1109/EMBC46164.2021.9630703>
- Aonpong, P., Iwamoto, Y., Wang, W., Lin, L., & Chen, Y.-W. (2020). Hand-Crafted and Deep Learning-Based Radiomics Models for Recurrence Prediction of Non-Small Cells Lung Cancers. *Innovation in Medicine and Healthcare*, 192, 135-144. doi:[https://doi.org/10.1007/978-981-15-5852-8\\_13](https://doi.org/10.1007/978-981-15-5852-8_13)
- Aonpong, P., Iwamoto, Y., Wang, W., Lin, L., & Chen, Y.-W. (2021). Genomics-Based Models for Recurrence Prediction of Non-small Cells Lung Cancers. Paper presented at the KES International Conferences on Innovation in Medicine and Healthcare (KES-InMed-21)
- Brummer, A. B., & Savage, V. M. (2021). Cancer as a Model System for Testing Metabolic Scaling Theory. *Frontiers in Ecology and Evolution*, 9. doi:10.3389/fevo.2021.691830
- Caruso, C. M., Guarrasi, V., Cordelli, E., Sicilia, R., Gentile, S., Messina, L., ... Soda, P. (2022). A Multimodal Ensemble Driven by Multiobjective Optimisation to Predict Overall Survival in Non-Small-Cell Lung Cancer. *J Imaging*, 8(11). doi:<https://doi.org/10.3390/jimaging8110298>
- Chen, W., Qiao, X., Yin, S., Zhang, X., & Xu, X. (2022). Integrating Radiomics with Genomics for Non-Small Cell Lung Cancer Survival Analysis. *J Oncol*, 2022, 5131170. doi:<https://doi.org/10.1155/2022/5131170>
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- Christie, J. R., Daher, O., Abdelrazek, M., Romine, P. E., Malthaner, R. A., Qiabi, M., . . . Mattonen, S. A. (2022). Predicting recurrence risks in lung cancer patients using multimodal radiomics and random survival forests. *J Med Imaging (Bellingham)*, 9(6), 066001. doi:<https://doi.org/10.1117/1.JMI.9.6.066001>
- Gui, D., Song, Q., Song, B., Li, H., Wang, M., Min, X., & Li, A. (2022). AIR-Net: A novel multi-task learning method with auxiliary image reconstruction for predicting EGFR mutation status on CT images of NSCLC patients. *Comput Biol Med*, 141, 105157. doi:10.1016/j.compbimed.2021.105157
- Hosny, A., Bitterman, D. S., Guthier, C. V., Qian, J. M., Roberts, H., Perni, S., . . . Mak, R. H. (2022). Clinical validation of deep learning algorithms for radiotherapy targeting of non-small-cell lung cancer: an observational study. *The Lancet Digital Health*, 4(9), e657-e666. doi:10.1016/S2589-7500(22)00129-7
- Ju, H. M., Kim, B. C., Lim, I., Byun, B. H., & Woo, S. K. (2023). Estimation of an Image Biomarker for Distant Recurrence Prediction in NSCLC Using Proliferation-Related Genes. *Int J Mol Sci*, 24(3). doi:<https://doi.org/10.3390/ijms24032794>
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- Mienye, I. D., Sun, Y., & Wang, Z. (2020). Improved Predictive Sparse Decomposition Method with Densenet for Prediction of Lung Cancer. *International Journal of Computing*, 19(4), 533-541. doi:10.47839/ijc.19.4.1986
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- Shiri, I., Amini, M., Nazari, M., Hajianfar, G., Haddadi Avval, A., Abdollahi, H., . . . Zaidi, H. (2022). Impact of feature harmonization on radiogenomics analysis: Prediction of EGFR and KRAS mutations from non-small cell lung cancer PET/CT images. *Comput Biol Med*, 142, 105230. doi:<https://doi.org/10.1016/j.compbiomed.2022.105230>
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- Thomas, R., Schalck, E., Fourure, D., Bonnefoy, A., & Cervera-Marzal, I. (2021). 2Be3-Net: Combining 2D and 3D Convolutional Neural Networks for 3D PET Scans Predictions. Paper presented at the International Conference on Medical Imaging and Computer-Aided Diagnosis (MICAD 2021).
- Torres, F. S., Akbar, S., Raman, S., Yasufuku, K., Schmidt, C., Hosny, A., . . . Leighl, N. B. (2021). End-to-End Non-Small-Cell Lung Cancer Prognostication Using Deep Learning Applied to Pretreatment Computed Tomography. *JCO Clin Cancer Inform*, 5, 1141-1150. doi:10.1200/cci.21.00096
- Trebeschi, S., Bodalal, Z., van Dijk, N., Boellaard, T. N., Apfaltrer, P., Tareco Bucho, T. M., . . . Beets-Tan, R. G. H. (2021). Development of a Prognostic AI-Monitor for Metastatic Urothelial Cancer Patients Receiving Immunotherapy. *Front Oncol*, 11, 637804. doi:10.3389/fonc.2021.637804
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- Wang, S. (2022). Multi-Modality Automatic Lung Tumor Segmentation Method Using Deep Learning and Radiomics. (Ph.D. Dissertation). Virginia Commonwealth University, Virginia, USA.
- Wang, Z., Yang, C., Han, W., Sui, X., Zheng, F., Xue, F., . . . Jiang, J. (2022). Quantifying lung cancer heterogeneity using novel CT features: a cross-institute study. *Insights Imaging*, 13(1), 82. doi:10.1186/s13244-022-01204-9

- Yousefi, B., Jahani, N., LaRiviere, M. J., Cohen, E., Hsieh, M.-K., Luna, J. M., . . . Kontos, D. (2019). Correlative hierarchical clustering-based low-rank dimensionality reduction of radiomics-driven phenotype in non-small cell lung cancer. Paper presented at the SPIE Medical Imaging, San Diego, California, United States.

If you have a manuscript you'd like to add please [contact TCIA's Helpdesk](#).

### **Versions**

#### **Version 4 (Current): Updated 2021/06/01**

| Data Type                  | Download all or Query/Filter                                                                                    |
|----------------------------|-----------------------------------------------------------------------------------------------------------------|
| Images (DICOM, 97.6 GB)    | <a href="#">Download</a> <a href="#">Search</a><br>(Download requires the <a href="#">NBIA Data Retriever</a> ) |
| AIM Annotations (XML, zip) | <a href="#">Download</a>                                                                                        |
| Clinical Data (csv)        | <a href="#">Download</a>                                                                                        |

- Added missing image studies for the following cases: R01-009 (CT), R01-100 (PET/CT), and R01-111 (PET/CT).
- SUV conversion factor DICOM tag (7053,1000) was added for the following Philips PET images: R01-074, R01-077, R01-079, R01-089, R01-98 and R01-137.

#### **Version 3: Updated 2020/11/10**

| Data Type                  | Download all or Query/Filter                                                          |
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| Images (DICOM, 97.6 GB)    | <a href="#">Download</a> (Download requires the <a href="#">NBIA Data Retriever</a> ) |
| AIM Annotations (XML, zip) | <a href="#">Download</a>                                                              |
| Clinical Data (csv)        | <a href="#">Download</a>                                                              |

- A new version of RO1-023 was created to correct a cranial-caudal flip of the segmentation of the CT volume (483 images) and associated Segmentation object. The UUIDs of the other scans were updated to preserve Study level consistency but were otherwise unmodified. The referenced UUIDs within the AIM object for RO1-023 were updated and renamed to RO1-023v1.
- RO1-038 was updated to remove a coronal slice at the start of the of the CT volume. This created difficulty for some software to determine slice spacing.

#### **Version 2: Updated 2017/02/28**

| Data Type                  | Download all or Query/Filter                                                          |
|----------------------------|---------------------------------------------------------------------------------------|
| Images (DICOM, 97.6 GB)    | <a href="#">Download</a> (Download requires the <a href="#">NBIA Data Retriever</a> ) |
| AIM Annotations (XML, zip) | <a href="#">Download</a>                                                              |
| Clinical Data (csv)        | <a href="#">Download</a>                                                              |

## Version 1: Updated 2015/12/22

This collection was originally submitted to TCIA as a 26 subject pilot data set. You can learn more about that subset of the collection in the following Analysis Results publication:

[NSCLC Radiogenomics: Initial Stanford Study of 26 Cases](#)

