Yoganand Balagurunathan

List of Publications by Year
in descending order

95 papers	7,168 citations	117625 34 h-index	62596 80 g-index
99 all docs	99 docs citations	99 times ranked	10284 citing authors

#	Article	IF	Citations
1	Volume doubling time and radiomic features predict tumor behavior of screen-detected lung cancers. Cancer Biomarkers, 2022, 33, 489-501.	1.7	4
2	Quantitative Measures of Background Parenchymal Enhancement Predict Breast Cancer Risk. American Journal of Roentgenology, 2021, 217, 64-75.	2.2	17
3	Requirements and reliability of AI in the medical context. Physica Medica, 2021, 83, 72-78.	0.7	30
4	Integrated Biomarkers for the Management of Indeterminate Pulmonary Nodules. American Journal of Respiratory and Critical Care Medicine, 2021, 204, 1306-1316.	5.6	36
5	Lung Nodule Malignancy Prediction in Sequential CT Scans: Summary of ISBI 2018 Challenge. IEEE Transactions on Medical Imaging, 2021, 40, 3748-3761.	8.9	13
6	High metabolic tumor volume is associated with decreased efficacy of axicabtagene ciloleucel in large B-cell lymphoma. Blood Advances, 2020, 4, 3268-3276.	5.2	134
7	Multi-Window CT Based Radiological Traits for Improving Early Detection in Lung Cancer Screening . Cancer Management and Research, 2020, Volume 12, 12225-12238.	1.9	3
8	¹⁸F-FDG PET/CT Habitat Radiomics Predicts Outcome of Patients with Cervical Cancer Treated with Chemoradiotherapy. Radiology: Artificial Intelligence, 2020, 2, e190218.	5.8	19
9	Repeatability of Quantitative Imaging Features in Prostate Magnetic Resonance Imaging. Frontiers in Oncology, 2020, 10, 551.	2.8	9
10	Peritumoral and intratumoral radiomic features predict survival outcomes among patients diagnosed in lung cancer screening. Scientific Reports, 2020, 10, 10528.	3.3	46
11	A shallow convolutional neural network predicts prognosis of lung cancer patients in multi-institutional computed tomography image datasets. Nature Machine Intelligence, 2020, 2, 274-282.	16.0	54
12	Standardization in Quantitative Imaging: A Multicenter Comparison of Radiomic Features from Different Software Packages on Digital Reference Objects and Patient Data Sets. Tomography, 2020, 6, 118-128.	1.8	61
13	Multiphase computed tomography radiomics of pancreatic intraductal papillary mucinous neoplasms to predict malignancy. World Journal of Gastroenterology, 2020, 26, 3458-3471.	3.3	34
14	Acidity promotes tumour progression by altering macrophage phenotype in prostate cancer. British Journal of Cancer, 2019, 121, 556-566.	6.4	86
15	Multi-window CT based Radiomic signatures in differentiating indolent versus aggressive lung cancers in the National Lung Screening Trial: a retrospective study. Cancer Imaging, 2019, 19, 45.	2.8	18
16	Semiautomated Measure of Abdominal Adiposity Using Computed Tomography Scan Analysis. Journal of Surgical Research, 2019, 237, 12-21.	1.6	2
17	Multiparameter MRI Predictors of Long-Term Survival in Glioblastoma Multiforme. Tomography, 2019, 5, 135-144.	1.8	28
18	Quantitative Imaging features Improve Discrimination of Malignancy in Pulmonary nodules. Scientific Reports, 2019, 9, 8528.	3.3	35

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19	OA02.08 Peritumoral and Intratumoral Radiomic Features Identify Aggressive Screen-Detected Early-Stage Lung Cancers. Journal of Thoracic Oncology, 2019, 14, S1130.	1.1	1
20	Radiological semantics discriminate clinically significant grade prostate cancer. Cancer Imaging, 2019, 19, 81.	2.8	7
21	Explaining Deep Features Using Radiologist-Defined Semantic Features and Traditional Quantitative Features. Tomography, 2019, 5, 192-200.	1.8	24
22	Habitats in DCE-MRI to Predict Clinically Significant Prostate Cancers. Tomography, 2019, 5, 68-76.	1.8	12
23	Prediction of pathological nodal involvement by <scp>CT</scp>â€based Radiomic features of the primary tumor in patients with clinically nodeâ€negative peripheral lung adenocarcinomas. Medical Physics, 2018, 45, 2518-2526.	3.0	26
24	Semiâ€automated pulmonary nodule interval segmentation using the <scp>NLST</scp> data. Medical Physics, 2018, 45, 1093-1107.	3.0	17
25	Perfusion MR Imaging of Breast Cancer: Insights Using â€œHabitat Imagingâ€. Radiology, 2018, 288, 36-37.	7.3	12
26	Comparison Between Radiological Semantic Features and Lung-RADS in Predicting Malignancy of Screen-Detected Lung Nodules in the National Lung Screening Trial. Clinical Lung Cancer, 2018, 19, 148-156.e3.	2.6	20
27	Radiologic Features of Small Pulmonary Nodules and Lung Cancer Risk in the National Lung Screening Trial: A Nested Case-Control Study. Radiology, 2018, 286, 298-306.	7.3	58
28	Representation of Deep Features using Radiologist defined Semantic Features. , 2018, 2018, .		2
29	Delta radiomic features improve prediction for lung cancer incidence: A nested caseâ€“control analysis of the National Lung Screening Trial. Cancer Medicine, 2018, 7, 6340-6356.	2.8	27
30	Radiomic biomarkers from PET/CT multi-modality fusion images for the prediction of immunotherapy response in advanced non-small cell lung cancer patients. , 2018, , .		16
31	Predicting clinically significant prostate cancer using DCE-MRI habitat descriptors. Oncotarget, 2018, 9, 37125-37136.	1.8	20
32	Abstract 3634: PET/CT imaging prediction of response to checkpoint blockade in advanced non-small cell lung cancer patients. , 2018, , .		0
33	Abstract B10: Radiomics signatures on the region defined by using multi-window CT to improve detection lung cancer screening. , 2018, , .		0
34	Intrinsic dependencies of <scp>CT</scp> radiomic features on voxel size and number of gray levels. Medical Physics, 2017, 44, 1050-1062.	3.0	428
35	Defining Cancer Subpopulations by Adaptive Strategies Rather Than Molecular Properties Provides Novel Insights into Intratumoral Evolution. Cancer Research, 2017, 77, 2242-2254.	0.9	110
36	Imaging features from pretreatment <scp>CT</scp> scans are associated with clinical outcomes in nonsmallâ€cell lung cancer patients treated with stereotactic body radiotherapy. Medical Physics, 2017, 44, 4341-4349.	3.0	53

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37	P1.01-041 Quantitative Imaging Features Predict Response of Immunotherapy in Non-Small Cell Lung Cancer Patients. Journal of Thoracic Oncology, 2017, 12, S474-S475.	1.1	3
38	P1.03-063 Quantitative Imaging Features Predict Incidence Lung Cancer in Low-Dose Computed Tomography (LDCT) Screening. Journal of Thoracic Oncology, 2017, 12, S582.	1.1	0
39	Linc-ing Circulating Long Non-coding RNAs to the Diagnosis and Malignant Prediction of Intraductal Papillary Mucinous Neoplasms of the Pancreas. Scientific Reports, 2017, 7, 10484.	3.3	60
40	Radiological Image Traits Predictive of Cancer Status in Pulmonary Nodules. Clinical Cancer Research, 2017, 23, 1442-1449.	7.0	76
41	PUB063 Epidemiologic and Radiomic Analysis of Hyperprogressers of Lung Cancer Patients Treated with Immunotherapy. Journal of Thoracic Oncology, 2017, 12, S2386.	1.1	1
42	CT imaging features associated with recurrence in non-small cell lung cancer patients after stereotactic body radiotherapy. Radiation Oncology, 2017, 12, 158.	2.7	63
43	Radial gradient and radial deviation radiomic features from pre-surgical CT scans are associated with survival among lung adenocarcinoma patients. Oncotarget, 2017, 8, 96013-96026.	1.8	26
44	Delineation of Tumor Habitats based on Dynamic Contrast Enhanced MRI. Scientific Reports, 2017, 7, 9746.	3.3	48
45	A pilot study of radiologic measures of abdominal adiposity: weighty contributors to early pancreatic carcinogenesis worth evaluating?. Cancer Biology and Medicine, 2017, 14, 66-73.	3.0	2
46	Radiomics of Lung Nodules: A Multi-Institutional Study of Robustness and Agreement of Quantitative Imaging Features. Tomography, 2016, 2, 430-437.	1.8	108
47	Deep Feature Transfer Learning in Combination with Traditional Features Predicts Survival among Patients with Lung Adenocarcinoma. Tomography, 2016, 2, 388-395.	1.8	128
48	Change descriptors for determining nodule malignancy in national lung screening trial CT screening images. , 2016, , .		0
49	Improving malignancy prediction through feature selection informed by nodule size ranges in NLST. , 2016, 2016, 001939-1944.		5
50	Radiomics of lung cancer. Journal of Thoracic Oncology, 2016, 11, S5-S6.	1.1	4
51	Association Between Computed Tomographic Features and Kirsten Rat Sarcoma Viral Oncogene Mutations in Patients With Stage I Lung Adenocarcinoma and Their Prognostic Value. Clinical Lung Cancer, 2016, 17, 271-278.	2.6	17
52	Predicting Malignant Nodules from Screening CT Scans. Journal of Thoracic Oncology, 2016, 11, 2120-2128.	1.1	226
53	Quantitative imaging features to predict cancer status in lung nodules. , 2016, , .		1
54	Performance comparison of quantitative semantic features and lung-RADS in the National Lung Screening Trial. , 2016, , .		0

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55	Diagnostic and predictive quantitative-imaging features in lung cancer screening. Journal of Thoracic Oncology, 2016, 11, S41-S42.	1.1	1
56	Radiomic Features Are Associated With EGFR Mutation Status in Lung Adenocarcinomas. Clinical Lung Cancer, 2016, 17, 441-448.e6.	2.6	264
57	CT Features Associated with Epidermal Growth Factor Receptor Mutation Status in Patients with Lung Adenocarcinoma. Radiology, 2016, 280, 271-280.	7.3	180
58	Differences in Patient Outcomes of Prevalence, Interval, and Screen-Detected Lung Cancers in the CT Arm of the National Lung Screening Trial. PLoS ONE, 2016, 11, e0159880.	2.5	46
59	Prostate cancer radiomics and the promise of radiogenomics. Translational Cancer Research, 2016, 5, 432-447.	1.0	111
60	MO-DE-207B-04: Impact of Reconstruction Field of View On Radiomics Features in Computed Tomography (CT) Using a Texture Phantom. Medical Physics, 2016, 43, 3705-3705.	3.0	5
61	Quantitative Computed Tomographic Descriptors Associate Tumor Shape Complexity and Intratumor Heterogeneity with Prognosis in Lung Adenocarcinoma. PLoS ONE, 2015, 10, e0118261.	2.5	207
62	Intermittent Hypoxia Selects for Genotypes and Phenotypes That Increase Survival, Invasion, and Therapy Resistance. PLoS ONE, 2015, 10, e0120958.	2.5	65
63	Predicting Outcomes of Nonsmall Cell Lung Cancer Using CT Image Features. IEEE Access, 2014, 2, 1418-1426.	4.2	104
64	Radiologically Defined Ecological Dynamics and Clinical Outcomes in Glioblastoma Multiforme: Preliminary Results. Translational Oncology, 2014, 7, 5-13.	3.7	82
65	Testâ€“Retest Reproducibility Analysis of Lung CT Image Features. Journal of Digital Imaging, 2014, 27, 805-823.	2.9	216
66	Mechanisms of buffer therapy resistance. Neoplasia, 2014, 16, 354-364.e3.	5.3	26
67	Reproducibility and Prognosis of Quantitative Features Extracted from CT Images. Translational Oncology, 2014, 7, 72-87.	3.7	258
68	Abstract 3250: Survival of patients with incident lung cancer following screening by computed tomography in the National Lung Screening Trial. , 2014, , .		1
69	SU-E-QI-17: Dependence of 3D/4D PET Quantitative Image Features On Noise. Medical Physics, 2014, 41, 380-380.	3.0	0
70	SU-E-QI-16: Reproducibility of Computed Tomography Quantitative Structural Features Using the FDA Thoracic Phantom Image Database. Medical Physics, 2014, 41, 380-380.	3.0	0
71	Laboratory Intercomparison of Gene Expression Assays. Radiation Research, 2013, 180, 138-148.	1.5	74
72	Acidity Generated by the Tumor Microenvironment Drives Local Invasion. Cancer Research, 2013, 73, 1524-1535.	0.9	1,036

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73	Comparison of Established and Emerging Biodosimetry Assays. Radiation Research, 2013, 180, 111-119.	1.5	123
74	Radiomics: the process and the challenges. Magnetic Resonance Imaging, 2012, 30, 1234-1248.	1.8	1,675
75	Estrogen induces apoptosis in estrogen deprivation-resistant breast cancer through stress responses as identified by global gene expression across time. Proceedings of the National Academy of Sciences of the United States of America, 2011, 108, 18879-18886.	7.1	151
76	Identification of Pancreatic Cancer-Specific Cell-Surface Markers for Development of Targeting Ligands. Methods in Molecular Biology, 2010, 624, 195-210.	0.9	3
77	Abstract 2744: Loss of VAV3 expression as a novel biomarker and indicator of chemosensitivity in basal-like breast cancer. , 2010, , .		0
78	Abstract P2-09-23: Investigating VAV3 Expression as a Novel Biomarker and Indicator of Chemosensitivity in Basal-Like Breast Cancer. , 2010, , .		0
79	siRNA screening: A process model to evaluate hit rate discovery. , 2008, , .		0
80	Gene expression profiling-based identification of cell-surface targets for developing multimeric ligands in pancreatic cancer. Molecular Cancer Therapeutics, 2008, 7, 3071-3080.	4.1	25
81	Insight into redox-regulated gene networks in vascular cells. Bioinformation, 2007, 1, 379-383.	0.5	7
82	Effect of normalization on microarray-based classification. , 2006, , .		0
83	Normalization Benefits Microarray-Based Classification. Eurasip Journal on Bioinformatics and Systems Biology, 2006, 2006, 1-13.	1.4	14
84	Epigenetic Transdifferentiation of Normal Melanocytes by a Metastatic Melanoma Microenvironment. Cancer Research, 2005, 65, 10164-10169.	0.9	61
85	Unraveling gene-gene interactions regulated by ligands of the aryl hydrocarbon receptor.. Environmental Health Perspectives, 2004, 112, 403-412.	6.0	54
86	Noise factor analysis for cDNA microarrays. Journal of Biomedical Optics, 2004, 9, 663.	2.6	21
87	Application of image-based granulometry to siliceous and calcareous estuarine and marine sediments. Estuarine, Coastal and Shelf Science, 2003, 58, 227-239.	2.1	10
88	Granulometric parametric estimation for the random Boolean model using optimal linear filters and optimal structuring elements. Pattern Recognition Letters, 2003, 24, 283-293.	4.2	4
89	Morphological quantification of surface roughness. Optical Engineering, 2003, 42, 1795.	1.0	10
90	Genomic profiles and predictive biological networks in oxidant-induced atherogenesis. Physiological Genomics, 2003, 13, 263-275.	2.3	34

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91	Simulation of cDNA microarrays via a parameterized random signal model. Journal of Biomedical Optics, 2002, 7, 507.	2.6	44
92	Optimal linear granulometric estimation for random sets. Pattern Recognition, 2002, 35, 1315-1325.	8.1	2
93	<title>Random signal model for cDNA microarrays</title>. , 2001, 4266, 163.		0
94	Asymptotic joint normality of the granulometric moments. Pattern Recognition Letters, 2001, 22, 1537-1543.	4.2	2
95	MORPHOLOGICAL GRANULOMETRIC ANALYSIS OF SEDIMENT IMAGES. Image Analysis and Stereology, 2001, 20, 87.	0.9	7