Spyridon Bakas

List of Publications by Year
in descending order

103 papers	7,058 citations	218677 26 h-index	62596 80 g-index
106 all docs	106 docs citations	106 times ranked	6693 citing authors

#	Article	IF	Citations
1	Quantifying T2-FLAIR Mismatch Using Geographically Weighted Regression and Predicting Molecular Status in Lower-Grade Gliomas. American Journal of Neuroradiology, 2022, 43, 33-39.	2.4	11
2	Classification of Infection and Ischemia in Diabetic Foot Ulcers Using VGG Architectures. Lecture Notes in Computer Science, 2022, 13183, 76-89.	1.3	6
3	Clinically Deployed Computational Assessment of Multiple Sclerosis Lesions. Frontiers in Medicine, 2022, 9, 797586.	2.6	4
4	Clinical measures, radiomics, and genomics offer synergistic value in AI-based prediction of overall survival in patients with glioblastoma. Scientific Reports, 2022, 12, .	3.3	20
5	Enhancing the REMBRANDT MRI collection with expert segmentation labels and quantitative radiomic features. Scientific Data, 2022, 9, .	5.3	1
6	The Medical Segmentation Decathlon. Nature Communications, 2022, 13, .	12.8	252
7	Analyzing magnetic resonance imaging data from glioma patients using deep learning. Computerized Medical Imaging and Graphics, 2021, 88, 101828.	5.8	23
8	Estimating Glioblastoma Biophysical Growth Parameters Using Deep Learning Regression. Lecture Notes in Computer Science, 2021, 12658, 157-167.	1.3	1
9	Accurate and Robust Alignment of Differently Stained Histologic Images Based on Greedy Diffeomorphic Registration. Applied Sciences (Switzerland), 2021, 11, 1892.	2.5	8
10	Radiomics analysis for predicting pembrolizumab response in patients with advanced rare cancers. , 2021, 9, e001752.		34
11	Author response to Cunha <i>et al</i>. , 2021, 9, e003299.		0
12	Interactive Machine Learning-Based Multi-Label Segmentation of Solid Tumors and Organs. Applied Sciences (Switzerland), 2021, 11, 7488.	2.5	5
13	NIMG-22. PREDICTION OF GLIOBLASTOMA CELLULAR INFILTRATION AND RECURRENCE USING MACHINE LEARNING AND MULTI-PARAMETRIC MRI ANALYSIS: RESULTS FROM THE MULTI-INSTITUTIONAL RESPOND CONSORTIUM. Neuro-Oncology, 2021, 23, vi132-vi133.	1.2	3
14	NIMG-28. PROSPECTIVE HISTOPATHOLOGY-VALIDATED MACHINE LEARNING FOR DISTINGUISHING TRUE PROGRESSION FROM TREATMENT-RELATED CHANGES IN GLIOBLASTOMA PATIENTS. Neuro-Oncology, 2021, 23, vi134-vi135.	1.2	0
15	EPCO-09. LONGITUDINAL ANALYSIS OF DIFFUSE GLIOMA REVEALS CELL STATE DYNAMICS AT RECURRENCE ASSOCIATED WITH CHANGES IN GENETICS AND THE MICROENVIRONMENT. Neuro-Oncology, 2021, 23, vi3-vi3.	1.2	0
16	NIMG-73. CAPTURING GLIOBLASTOMA HETEROGENEITY USING IMAGING AND DEEP LEARNING: APPLICATION TO MGMT PROMOTER METHYLATION. Neuro-Oncology, 2021, 23, vi146-vi146.	1.2	3
17	EPCO-25. MULTI-OMICS DISEASE STRATIFICATION IN PATIENTS WITH IDH-WILDTYPE GLIOBLASTOMA: SYNERGISTIC VALUE OF CLINICAL MEASURES, CONVENTIONAL AND DEEP RADIOMICS, AND GENOMICS FOR PREDICTION OF OVERALL SURVIVAL. Neuro-Oncology, 2021, 23, vi7-vi7.	1.2	1
18	NIMG-55. AUGMENTED INTELLIGENCE IS SUPERIOR TO ARTIFICIAL INTELLIGENCE! HUMAN-COMPUTER SYNERGY FOR GENERATING HIGH QUALITY GLIOBLASTOMA SUB-REGION SEGMENTATIONS. Neuro-Oncology, 2021, 23, vi141-vi142.	1.2	0

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19	Applications of Radiomics and Radiogenomics in High-Grade Gliomas in the Era of Precision Medicine. Cancers, 2021, 13, 5921.	3.7	29
20	NIMG-32. THE FEDERATED TUMOR SEGMENTATION (FETS) INITIATIVE: THE FIRST REAL-WORLD LARGE-SCALE DATA-PRIVATE COLLABORATION FOCUSING ON NEURO-ONCOLOGY. Neuro-Oncology, 2021, 23, vi135-vi136.	1.2	6
21	NIMG-58. CANONICAL CORRELATION ANALYSIS IN GLIOBLASTOMA REVEALS ASSOCIATIONS BETWEEN EXPRESSION OF RADIOMIC SIGNATURES AND GENOMICS. Neuro-Oncology, 2021, 23, vi142-vi142.	1.2	0
22	NIMG-52. RADIOGENOMICS SIGNATURES IN KEY DRIVER GENES IN GLIOBLASTOMA EVALUATED WITH AND WITHOUT THE PRESENCE OF CO-OCCURRING MUTATIONS. Neuro-Oncology, 2021, 23, vi141-vi141.	1.2	0
23	NIMG-39. RADIOMIC ANALYSIS FOR NON-INVASIVE IN VIVO PROGNOSTIC STRATIFICATION OF DE NOVO GLIOBLASTOMA PATIENTS: A MULTI-INSTITUTIONAL EVALUATION FOR GENERALIZABILITY IN THE RESPOND CONSORTIUM. Neuro-Oncology, 2021, 23, vi137-vi137.	1.2	0
24	Robust, Primitive, and Unsupervised Quality Estimation for Segmentation Ensembles. Frontiers in Neuroscience, 2021, 15, 752780.	2.8	4
25	Longitudinal brain tumor segmentation prediction in MRI using feature and label fusion. Biomedical Signal Processing and Control, 2020, 55, 101648.	5.7	42
26	Imaging signatures of glioblastoma molecular characteristics: A radiogenomics review. Journal of Magnetic Resonance Imaging, 2020, 52, 54-69.	3.4	61
27	Federated learning in medicine: facilitating multi-institutional collaborations without sharing patient data. Scientific Reports, 2020, 10, 12598.	3.3	509
28	Reproducibility analysis of multiâ€institutional paired expert annotations and radiomic features of the Ivy Glioblastoma Atlas Project (Ivy GAP) dataset. Medical Physics, 2020, 47, 6039-6052.	3.0	25
29	The future of digital health with federated learning. Npj Digital Medicine, 2020, 3, 119.	10.9	887
30	Integrated Biophysical Modeling and Image Analysis: Application to Neuro-Oncology. Annual Review of Biomedical Engineering, 2020, 22, 309-341.	12.3	39
31	The Image Biomarker Standardization Initiative: Standardized Quantitative Radiomics for High-Throughput Image-based Phenotyping. Radiology, 2020, 295, 328-338.	7.3	1,869
32	AI-based prognostic imaging biomarkers for precision neuro-oncology: the ReSPOND consortium. Neuro-Oncology, 2020, 22, 886-888.	1.2	31
33	Cancer Imaging Phenomics via CaPTk: Multi-Institutional Prediction of Progression-Free Survival and Pattern of Recurrence in Glioblastoma. JCO Clinical Cancer Informatics, 2020, 4, 234-244.	2.1	26
34	Histopathologyâ€validated machine learning radiographic biomarker for noninvasive discrimination between true progression and pseudoâ€progression in glioblastoma. Cancer, 2020, 126, 2625-2636.	4.1	60
35	Brain extraction on MRI scans in presence of diffuse glioma: Multi-institutional performance evaluation of deep learning methods and robust modality-agnostic training. NeuroImage, 2020, 220, 117081.	4.2	35
36	iGLASS: imaging integration into the Glioma Longitudinal Analysis Consortium. Neuro-Oncology, 2020, 22, 1545-1546.	1.2	12

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37	Segmentation and Classification in Digital Pathology for Glioma Research: Challenges and Deep Learning Approaches. Frontiers in Neuroscience, 2020, 14, 27.	2.8	54
38	ANHIR: Automatic Non-Rigid Histological Image Registration Challenge. IEEE Transactions on Medical Imaging, 2020, 39, 3042-3052.	8.9	75
39	Skull-Stripping of Glioblastoma MRI Scans Using 3D Deep Learning. Lecture Notes in Computer Science, 2020, 11992, 57-68.	1.3	11
40	The Cancer Imaging Phenomics Toolkit (CaPTk): Technical Overview. Lecture Notes in Computer Science, 2020, 11993, 380-394.	1.3	34
41	NIMG-66. AI-BASED PROGNOSTIC IMAGING BIOMARKERS FOR PRECISION NEUROONCOLOGY AND THE RESPOND CONSORTIUM. Neuro-Oncology, 2020, 22, ii162-ii163.	1.2	3
42	Overall survival prediction in glioblastoma patients using structural magnetic resonance imaging (MRI): advanced radiomic features may compensate for lack of advanced MRI modalities. Journal of Medical Imaging, 2020, 7, 1.	1.5	26
43	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
44	Systematic Evaluation of Image Tiling Adverse Effects on Deep Learning Semantic Segmentation. Frontiers in Neuroscience, 2020, 14, 65.	2.8	27
45	Multi-institutional noninvasive in vivo characterization of <i>IDH</i>, 1p/19q, and EGFRvIII in glioma using neuro-Cancer Imaging Phenomics Toolkit (neuro-CaPTk). Neuro-Oncology Advances, 2020, 2, iv22-iv34.	0.7	12
46	A Deep Network for Joint Registration and Reconstruction of Images with Pathologies. Lecture Notes in Computer Science, 2020, 12436, 342-352.	1.3	7
47	Towards Population-Based Histologic Stain Normalization of Glioblastoma. Lecture Notes in Computer Science, 2020, 11992, 44-56.	1.3	3
48	O-Net: An Overall Convolutional Network for Segmentation Tasks. Lecture Notes in Computer Science, 2020, 12436, 199-209.	1.3	3
49	Integrative radiomic analysis for pre-surgical prognostic stratification of glioblastoma patients: from advanced to basic MRI protocols. , 2020, 11315, .		4
50	EPID-20. NOVEL GLIOBLASTOMA POPULATION-BASED HISTOLOGIC STAIN NORMALIZATION. Neuro-Oncology, 2020, 22, ii82-ii83.	1.2	0
51	NIMG-40. RADIOGENOMIC SIGNATURES OF DRIVER GENES IN NEWLY DIAGNOSED GLIOBLASTOMA PATIENTS BASED ON PRE-OPERATIVE MULTI-PARAMETRIC MRI. Neuro-Oncology, 2020, 22, ii156-ii157.	1.2	0
52	NIMG-09. PREDICTING OVERALL SURVIVAL OF GLIOBLASTOMA PATIENTS ON MULTI-INSTITUTIONAL HISTOPATHOLOGY STAINED SLIDES USING DEEP LEARNING AND POPULATION-BASED NORMALIZATION. Neuro-Oncology, 2020, 22, ii148-ii148.	1.2	0
53	TMOD-09. GLIOBLASTOMA BIOPHYSICAL GROWTH ESTIMATION USING DEEP LEARNING-BASED REGRESSION. Neuro-Oncology, 2020, 22, ii229-ii229.	1.2	1
54	Computational staining of unlabelled tissue. Nature Biomedical Engineering, 2019, 3, 425-426.	22.5	3

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55	Precision diagnostics based on machine learning-derived imaging signatures. Magnetic Resonance Imaging, 2019, 64, 49-61.	1.8	31
56	Multi-stage Association Analysis of Glioblastoma Gene Expressions with Texture and Spatial Patterns. Lecture Notes in Computer Science, 2019, 11383, 239-250.	1.3	9
57	Evaluation of Indirect Methods for Motion Compensation in 2-D Focal Liver Lesion Contrast-Enhanced Ultrasound (CEUS) Imaging. Ultrasound in Medicine and Biology, 2019, 45, 1380-1396.	1.5	7
58	Multi-institutional Deep Learning Modeling Without Sharing Patient Data: A Feasibility Study on Brain Tumor Segmentation. Lecture Notes in Computer Science, 2019, 11383, 92-104.	1.3	215
59	NIMG-40. ROBUST MODALITY-AGNOSTIC SKULL-STRIPPING IN PRESENCE OF DIFFUSE GLIOMA: A MULTI-INSTITUTIONAL STUDY. Neuro-Oncology, 2019, 21, vi170-vi170.	1.2	2
60	NIMG-35. QUANTITATIVE ESTIMATION OF PROGRESSION-FREE SURVIVAL BASED ON RADIOMICS ANALYSIS OF PREOPERATIVE MULTI-PARAMETRIC MRI IN PATIENTS WITH GLIOBLASTOMA. Neuro-Oncology, 2019, 21, vi168-vi169.	1.2	1
61	NIMG-59. ADVERSE EFFECTS OF IMAGE TILING FOR AUTOMATIC DEEP LEARNING GLIOMA SEGMENTATION IN MRI. Neuro-Oncology, 2019, 21, vi174-vi174.	1.2	0
62	NIMG-68. FEDERATED LEARNING IN NEURO-ONCOLOGY FOR MULTI-INSTITUTIONAL COLLABORATIONS WITHOUT SHARING PATIENT DATA. Neuro-Oncology, 2019, 21, vi176-vi177.	1.2	3
63	Multi-Disease Segmentation of Gliomas and White Matter Hyperintensities in the BraTS Data Using a 3D Convolutional Neural Network. Frontiers in Computational Neuroscience, 2019, 13, 84.	2.1	30
64	Multivariate Analysis of Preoperative Magnetic Resonance Imaging Reveals Transcriptomic Classification of de novo Glioblastoma Patients. Frontiers in Computational Neuroscience, 2019, 13, 81.	2.1	5
65	Patient-Specific Registration of Pre-operative and Post-recurrence Brain Tumor MRI Scans. Lecture Notes in Computer Science, 2019, 11383, 105-114.	1.3	6
66	Non-invasive transcriptomic classification of de novo Glioblastoma patients through multivariate quantitative analysis of baseline preoperative multimodal magnetic resonance imaging. , 2019, , .		0
67	Abstract 1392: Machine Learning Radiomic Biomarkers Non-invasively Assess Genetic Characteristics of Glioma Patients. Cancer Research, 2019, 79, 1392-1392.	0.9	4
68	Tumor segmentation. , 2019, , 99-114.		1
69	Abstract 1392: Machine Learning Radiomic Biomarkers Non-invasively Assess Genetic Characteristics of Glioma Patients. , 2019, , .		0
70	Brain Cancer Imaging Phenomics Toolkit (brain-CaPTk): An Interactive Platform for Quantitative Analysis of Glioblastoma. Lecture Notes in Computer Science, 2018, 10670, 133-145.	1.3	32
71	Use of Fetal Magnetic Resonance Image Analysis and Machine Learning to Predict the Need for Postnatal Cerebrospinal Fluid Diversion in Fetal Ventriculomegaly. JAMA Pediatrics, 2018, 172, 128.	6.2	20
72	<i>In vivo</i>evaluation of EGFRvIII mutation in primary glioblastoma patients via complex multiparametric MRI signature. Neuro-Oncology, 2018, 20, 1068-1079.	1.2	90

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73	NIMG-44. QUANTITATIVE MULTI-PARAMETRIC IMAGE PROFILING REVEALS REMARKABLE HETEROGENEITY WITHIN IDH-WILDTYPE GLIOBLASTOMA, OFFERING PROGNOSTIC STRATIFICATION BEYOND CURRENT WHO CLASSIFICATIONS. Neuro-Oncology, 2018, 20, vi186-vi186.	1.2	0
74	NIMG-70. QUANTITATIVE IMAGE ANALYSIS AND MACHINE LEARNING TECHNIQUES FOR DISTINGUISHING TRUE PROGRESSION FROM PSEUDOPROGRESSION IN PATIENTS WITH GLIOBLASTOMA. Neuro-Oncology, 2018, 20, vi191-vi192.	1.2	7
75	CSIG-25. EPIDERMAL GROWTH FACTOR RECEPTOR EXTRACELLULAR DOMAIN MISSENSE MUTATION A289V AS A DRIVER OF GLIOBLASTOMA INVASION AND PROLIFERATION. Neuro-Oncology, 2018, 20, vi48-vi48.	1.2	0
76	NIMG-38. QUANTITATIVE IMAGING PREDICTORS OF OVERALL SURVIVAL IN GLIOBLASTOMA PATIENTS ROBUST IN THE PRESENCE OF INTER-SCANNER VARIATIONS. Neuro-Oncology, 2018, 20, vi184-vi184.	1.2	3
77	NIMG-45. MULTIVARIATE PATTERN ANALYSIS OF DE NOVO GLIOBLASTOMA PATIENTS OFFERS IN VIVO EVALUATION OF O6-METHYLGUANINE-DNA-METHYLTRANSFERASE (MGMT) PROMOTER METHYLATION STATUS, COMPENSATING FOR INSUFFICIENT SPECIMEN AND ASSAY FAILURES. Neuro-Oncology, 2018, 20, vi186-vi186.	1.2	0
78	NIMG-40. NON-INVASIVE IN VIVO SIGNATURE OF IDH1 MUTATIONAL STATUS IN HIGH GRADE GLIOMA, FROM CLINICALLY-ACQUIRED MULTI-PARAMETRIC MAGNETIC RESONANCE IMAGING, USING MULTIVARIATE MACHINE LEARNING. Neuro-Oncology, 2018, 20, vi184-vi185.	1.2	6
79	Epidermal Growth Factor Receptor Extracellular Domain Mutations in Glioblastoma Present Opportunities for Clinical Imaging and Therapeutic Development. Cancer Cell, 2018, 34, 163-177.e7.	16.8	145
80	Brain extraction from normal and pathological images: A joint PCA/Image-Reconstruction approach. NeuroImage, 2018, 176, 431-445.	4.2	20
81	Cancer imaging phenomics toolkit: quantitative imaging analytics for precision diagnostics and predictive modeling of clinical outcome. Journal of Medical Imaging, 2018, 5, 1.	1.5	110
82	Deriving stable multi-parametric MRI radiomic signatures in the presence of inter-scanner variations: survival prediction of glioblastoma via imaging pattern analysis and machine learning techniques. , 2018, , .		1
83	Non-invasive determination of the O6-methylguanine-DNA-methyltransferase (MGMT) promoter methylation status in glioblastoma (GBM) using magnetic resonance imaging (MRI).. Journal of Clinical Oncology, 2018, 36, 2051-2051.	1.6	6
84	Advanced Magnetic Resonance Imaging in Glioblastoma: A Review. JHN Journal, 2018, 13, .	0.0	2
85	Fast semi-automatic segmentation of focal liver lesions in contrast-enhanced ultrasound, based on a probabilistic model. Computer Methods in Biomechanics and Biomedical Engineering: Imaging and Visualization, 2017, 5, 329-338.	1.9	14
86	Correlations of atrial diameter and frontooccipital horn ratio with ventricle size in fetal ventriculomegaly. Journal of Neurosurgery: Pediatrics, 2017, 19, 300-306.	1.3	12
87	<i>In Vivo</i> Detection of EGFRvIII in Glioblastoma via Perfusion Magnetic Resonance Imaging Signature Consistent with Deep Peritumoral Infiltration: The <i>Ï•</i>-Index. Clinical Cancer Research, 2017, 23, 4724-4734.	7.0	79
88	Advancing The Cancer Genome Atlas glioma MRI collections with expert segmentation labels and radiomic features. Scientific Data, 2017, 4, 170117.	5.3	1,555
89	Automatic Identification of the Optimal Reference Frame for Segmentation and Quantification of Focal Liver Lesions in Contrast-Enhanced Ultrasound. Ultrasound in Medicine and Biology, 2017, 43, 2438-2451.	1.5	6
90	NIMG-07. UNIFYING MAGNETIC RESONANCE IMAGING SIGNATURE OF EGFR PATHWAY ACTIVATION IN GLIOBLASTOMA CONSISTENT WITH UNIFORMLY AGGRESSIVELY INFILTRATION. Neuro-Oncology, 2017, 19, vi143-vi143.	1.2	1

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91	EXTH-56. EGFR EXTRACELLULAR DOMAIN POINT MUTANT A289V: AÂTHERAPEUTICALLY TARGETABLE DRIVER OF GLIOBLASTOMA INVASION. Neuro-Oncology, 2017, 19, vi85-vi85.	1.2	1
92	SCDT-37. MODULATION OF CONVECTION ENHANCED DELIVERY (CED) DISTRIBUTION USING FOCUSED ULTRASOUND (FUS). Neuro-Oncology, 2017, 19, vi272-vi272.	1.2	2
93	Advanced magnetic resonance imaging in glioblastoma: a review. Chinese Clinical Oncology, 2017, 6, 40-40.	1.2	119
94	NIMG-11. HIGHLY-EXPRESSED WILD-TYPE EGFR AND EGFRvIII MUTANT GLIOBLASTOMAS HAVE SIMILAR MRI SIGNATURE, CONSISTENT WITH DEEP PERITUMORAL INFILTRATION. Neuro-Oncology, 2016, 18, vi125-vi126.	1.2	5
95	MPTH-02. EXTRACELLULAR EGFR289 ACTIVATING MUTATIONS CONFER POORER SURVIVAL AND SUGGEST ENHANCED MOTILITY IN PRIMARY GBMs. Neuro-Oncology, 2016, 18, vi105-vi106.	1.2	7
96	Segmentation of Gliomas in Pre-operative and Post-operative Multimodal Magnetic Resonance Imaging Volumes Based on a Hybrid Generative-Discriminative Framework. Lecture Notes in Computer Science, 2016, 10154, 184-194.	1.3	27
97	GLISTRboost: Combining Multimodal MRI Segmentation, Registration, and Biophysical Tumor Growth Modeling with Gradient Boosting Machines for Glioma Segmentation. Lecture Notes in Computer Science, 2016, , 144-155.	1.3	61
98	NIMG-20. IMAGING PATTERN ANALYSIS REVEALS THREE DISTINCT PHENOTYPIC SUBTYPES OF GBM WITH DIFFERENT SURVIVAL RATES. Neuro-Oncology, 2016, 18, vi128-vi128.	1.2	10
99	Brain Lesions, Introduction. Lecture Notes in Computer Science, 2016, 9556, 1-5.	1.3	48
100	NIMG-05IDENTIFICATION OF IMAGING SIGNATURES OF THE EPIDERMAL GROWTH FACTOR RECEPTOR VARIANT III (EGFRvIII) IN GLIOBLASTOMA. Neuro-Oncology, 2015, 17, v154.1-v154.	1.2	5
101	Making the Best Use of Fifty (or More) Shades of Gray: Intelligent Contrast Optimisation for Image Segmentation in False-Colour Video. , 2014, , .		0
102	Spot the Best Frame: Towards Intelligent Automated Selection of the Optimal Frame for Initialisation of Focal Liver Lesion Candidates in Contrast-Enhanced Ultrasound Video Sequences. , 2013, , .		8
103	Focal Liver Lesion Tracking in CEUS for Characterisation Based on Dynamic Behaviour. Lecture Notes in Computer Science, 2012, , 32-41.	1.3	6