# Spyridon Bakas

List of Publications by Year
in descending order

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

| # | Article | IF | Citations |
|---|---|---|---|
| 1 | The Image Biomarker Standardization Initiative: Standardized Quantitative Radiomics for High-Throughput Image-based Phenotyping. Radiology, 2020, 295, 328-338. | 7.3 | 1,869 |
| 2 | Advancing The Cancer Genome Atlas glioma MRI collections with expert segmentation labels and radiomic features. Scientific Data, 2017, 4, 170117. | 5.3 | 1,555 |
| 3 | The future of digital health with federated learning. Npj Digital Medicine, 2020, 3, 119. | 10.9 | 887 |
| 4 | Federated learning in medicine: facilitating multi-institutional collaborations without sharing patient data. Scientific Reports, 2020, 10, 12598. | 3.3 | 509 |
| 5 | The Medical Segmentation Decathlon. Nature Communications, 2022, 13, . | 12.8 | 252 |
| 6 | 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 |
| 7 | 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 |
| 8 | Advanced magnetic resonance imaging in glioblastoma: a review. Chinese Clinical Oncology, 2017, 6, 40-40. | 1.2 | 119 |
| 9 | 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 |
| 10 | <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 |
| 11 | <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 |
| 12 | ANHIR: Automatic Non-Rigid Histological Image Registration Challenge. IEEE Transactions on Medical Imaging, 2020, 39, 3042-3052. | 8.9 | 75 |
| 13 | 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 |
| 14 | Imaging signatures of glioblastoma molecular characteristics: A radiogenomics review. Journal of Magnetic Resonance Imaging, 2020, 52, 54-69. | 3.4 | 61 |
| 15 | 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 |
| 16 | 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 |
| 17 | Segmentation and Classification in Digital Pathology for Glioma Research: Challenges and Deep Learning Approaches. Frontiers in Neuroscience, 2020, 14, 27. | 2.8 | 54 |
| 18 | Brain Lesions, Introduction. Lecture Notes in Computer Science, 2016, 9556, 1-5. | 1.3 | 48 |

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|---|---|---|---|
| 19 | Longitudinal brain tumor segmentation prediction in MRI using feature and label fusion. Biomedical Signal Processing and Control, 2020, 55, 101648. | 5.7 | 42 |
| 20 | Integrated Biophysical Modeling and Image Analysis: Application to Neuro-Oncology. Annual Review of Biomedical Engineering, 2020, 22, 309-341. | 12.3 | 39 |
| 21 | 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 |
| 22 | Radiomics analysis for predicting pembrolizumab response in patients with advanced rare cancers. , 2021, 9, e001752. | | 34 |
| 23 | The Cancer Imaging Phenomics Toolkit (CaPTk): Technical Overview. Lecture Notes in Computer Science, 2020, 11993, 380-394. | 1.3 | 34 |
| 24 | 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 |
| 25 | Precision diagnostics based on machine learning-derived imaging signatures. Magnetic Resonance Imaging, 2019, 64, 49-61. | 1.8 | 31 |
| 26 | AI-based prognostic imaging biomarkers for precision neuro-oncology: the ReSPOND consortium. Neuro-Oncology, 2020, 22, 886-888. | 1.2 | 31 |
| 27 | 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 |
| 28 | Applications of Radiomics and Radiogenomics in High-Grade Gliomas in the Era of Precision Medicine. Cancers, 2021, 13, 5921. | 3.7 | 29 |
| 29 | 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 |
| 30 | Systematic Evaluation of Image Tiling Adverse Effects on Deep Learning Semantic Segmentation. Frontiers in Neuroscience, 2020, 14, 65. | 2.8 | 27 |
| 31 | 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 |
| 32 | 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 |
| 33 | 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 |
| 34 | Analyzing magnetic resonance imaging data from glioma patients using deep learning. Computerized Medical Imaging and Graphics, 2021, 88, 101828. | 5.8 | 23 |
| 35 | 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 |
| 36 | Brain extraction from normal and pathological images: A joint PCA/Image-Reconstruction approach. NeuroImage, 2018, 176, 431-445. | 4.2 | 20 |

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| 37 | 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 |
| 38 | 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 |
| 39 | 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 |
| 40 | iGLASS: imaging integration into the Glioma Longitudinal Analysis Consortium. Neuro-Oncology, 2020, 22, 1545-1546. | 1.2 | 12 |
| 41 | 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 |
| 42 | Skull-Stripping of Glioblastoma MRI Scans Using 3D Deep Learning. Lecture Notes in Computer Science, 2020, 11992, 57-68. | 1.3 | 11 |
| 43 | 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 |
| 44 | 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 |
| 45 | 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 |
| 46 | 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 |
| 47 | Accurate and Robust Alignment of Differently Stained Histologic Images Based on Greedy Diffeomorphic Registration. Applied Sciences (Switzerland), 2021, 11, 1892. | 2.5 | 8 |
| 48 | 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 |
| 49 | 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 |
| 50 | 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 |
| 51 | A Deep Network for Joint Registration and Reconstruction of Images with Pathologies. Lecture Notes in Computer Science, 2020, 12436, 342-352. | 1.3 | 7 |
| 52 | 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 |
| 53 | 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 |
| 54 | Focal Liver Lesion Tracking in CEUS for Characterisation Based on Dynamic Behaviour. Lecture Notes in Computer Science, 2012, , 32-41. | 1.3 | 6 |

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| 55 | 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 |
| 56 | 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 |
| 57 | Classification of Infection and Ischemia in Diabetic Foot Ulcers Using VGG Architectures. Lecture Notes in Computer Science, 2022, 13183, 76-89. | 1.3 | 6 |
| 58 | 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 |
| 59 | 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 |
| 60 | 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 |
| 61 | 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 |
| 62 | Interactive Machine Learning-Based Multi-Label Segmentation of Solid Tumors and Organs. Applied Sciences (Switzerland), 2021, 11, 7488. | 2.5 | 5 |
| 63 | Abstract 1392: Machine Learning Radiomic Biomarkers Non-invasively Assess Genetic Characteristics of Glioma Patients. Cancer Research, 2019, 79, 1392-1392. | 0.9 | 4 |
| 64 | Integrative radiomic analysis for pre-surgical prognostic stratification of glioblastoma patients: from advanced to basic MRI protocols. , 2020, 11315, . | | 4 |
| 65 | Clinically Deployed Computational Assessment of Multiple Sclerosis Lesions. Frontiers in Medicine, 2022, 9, 797586. | 2.6 | 4 |
| 66 | Robust, Primitive, and Unsupervised Quality Estimation for Segmentation Ensembles. Frontiers in Neuroscience, 2021, 15, 752780. | 2.8 | 4 |
| 67 | 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 |
| 68 | Computational staining of unlabelled tissue. Nature Biomedical Engineering, 2019, 3, 425-426. | 22.5 | 3 |
| 69 | NIMG-68. FEDERATED LEARNING IN NEURO-ONCOLOGY FOR MULTI-INSTITUTIONAL COLLABORATIONS WITHOUT SHARING PATIENT DATA. Neuro-Oncology, 2019, 21, vi176-vi177. | 1.2 | 3 |
| 70 | NIMG-66. AI-BASED PROGNOSTIC IMAGING BIOMARKERS FOR PRECISION NEUROONCOLOGY AND THE RESPOND CONSORTIUM. Neuro-Oncology, 2020, 22, ii162-ii163. | 1.2 | 3 |
| 71 | Towards Population-Based Histologic Stain Normalization of Glioblastoma. Lecture Notes in Computer Science, 2020, 11992, 44-56. | 1.3 | 3 |
| 72 | O-Net: An Overall Convolutional Network for Segmentation Tasks. Lecture Notes in Computer Science, 2020, 12436, 199-209. | 1.3 | 3 |

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|---|---|---|---|
| 73 | 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 |
| 74 | NIMG-73. CAPTURING GLIOBLASTOMA HETEROGENEITY USING IMAGING AND DEEP LEARNING: APPLICATION TO MGMT PROMOTER METHYLATION. Neuro-Oncology, 2021, 23, vi146-vi146. | 1.2 | 3 |
| 75 | SCDT-37. MODULATION OF CONVECTION ENHANCED DELIVERY (CED) DISTRIBUTION USING FOCUSED ULTRASOUND (FUS). Neuro-Oncology, 2017, 19, vi272-vi272. | 1.2 | 2 |
| 76 | 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 |
| 77 | Advanced Magnetic Resonance Imaging in Glioblastoma: A Review. JHN Journal, 2018, 13, . | 0.0 | 2 |
| 78 | 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 |
| 79 | EXTH-56. EGFR EXTRACELLULAR DOMAIN POINT MUTANT A289V: AÂTHERAPEUTICALLY TARGETABLE DRIVER OF GLIOBLASTOMA INVASION. Neuro-Oncology, 2017, 19, vi85-vi85. | 1.2 | 1 |
| 80 | 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 |
| 81 | Estimating Glioblastoma Biophysical Growth Parameters Using Deep Learning Regression. Lecture Notes in Computer Science, 2021, 12658, 157-167. | 1.3 | 1 |
| 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 | Tumor segmentation. , 2019, , 99-114. | | 1 |
| 84 | 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 |
| 85 | TMOD-09. GLIOBLASTOMA BIOPHYSICAL GROWTH ESTIMATION USING DEEP LEARNING-BASED REGRESSION. Neuro-Oncology, 2020, 22, ii229-ii229. | 1.2 | 1 |
| 86 | Enhancing the REMBRANDT MRI collection with expert segmentation labels and quantitative radiomic features. Scientific Data, 2022, 9, . | 5.3 | 1 |
| 87 | Making the Best Use of Fifty (or More) Shades of Gray: Intelligent Contrast Optimisation for Image Segmentation in False-Colour Video. , 2014, , . | | 0 |
| 88 | 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 |
| 89 | 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 |
| 90 | 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 |

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| 91 | NIMG-59. ADVERSE EFFECTS OF IMAGE TILING FOR AUTOMATIC DEEP LEARNING GLIOMA SEGMENTATION IN MRI. Neuro-Oncology, 2019, 21, vi174-vi174. | 1.2 | 0 |
| 92 | Author response to Cunha <i>et al</i>. , 2021, 9, e003299. | | 0 |
| 93 | Non-invasive transcriptomic classification of de novo Glioblastoma patients through multivariate quantitative analysis of baseline preoperative multimodal magnetic resonance imaging. , 2019, , . | | 0 |
| 94 | 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 |
| 95 | 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 |
| 96 | 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 |
| 97 | EPID-20. NOVEL GLIOBLASTOMA POPULATION-BASED HISTOLOGIC STAIN NORMALIZATION. Neuro-Oncology, 2020, 22, ii82-ii83. | 1.2 | 0 |
| 98 | 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 |
| 99 | 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 |
| 100 | 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 |
| 101 | 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 |
| 102 | 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 |
| 103 | Abstract 1392: Machine Learning Radiomic Biomarkers Non-invasively Assess Genetic Characteristics of Glioma Patients. , 2019, , . | | 0 |