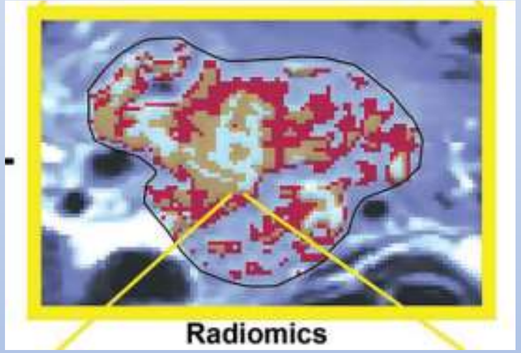
Radiomic Analysis and prognostication-TMH &Indian Data

Jayant S Goda, MD, DNB, MRes
Radiation Oncology
Email: godajayantsastri@gmail.com

Multi-modality Imaging in Cancer

Radiomic features

(**quantitative** features from medical images using **automated data characterization algorithms)**



- Machine learning algorithms
- Deep learning algorithms

Dosiomic features

radiomic features extracted

from **dose maps**

descriptors of **spatial patterns** in dose distributions

Semantic features

(**qualitative imaging** features that are defined by experienced **radiologists)**

- Diagnosis
- Disease classification
- Response to therapy
- Prognosis
- Toxicity
- Precision medicine
- Drug discovery

Indian Data : Radiomics & AI across all cancers

- Data has just started emerging from Indian institutions
- Mostly computational and organizational data
- Limited clinical Data
- Ongoing studies at various centres across India

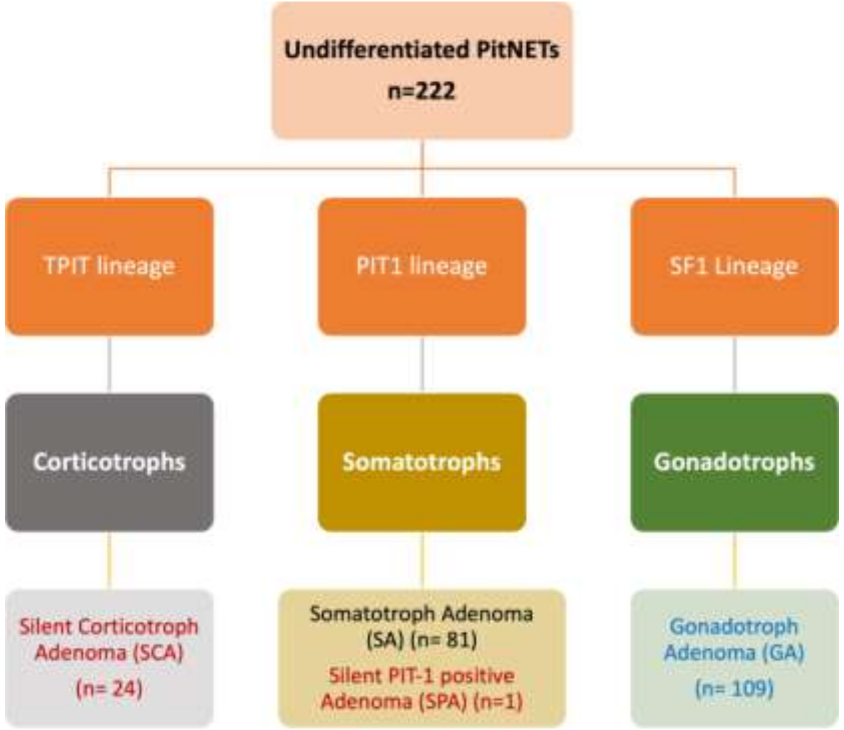
CMC, Tata Medical Centre, Tata Memorial hospital, other Centres across India……….

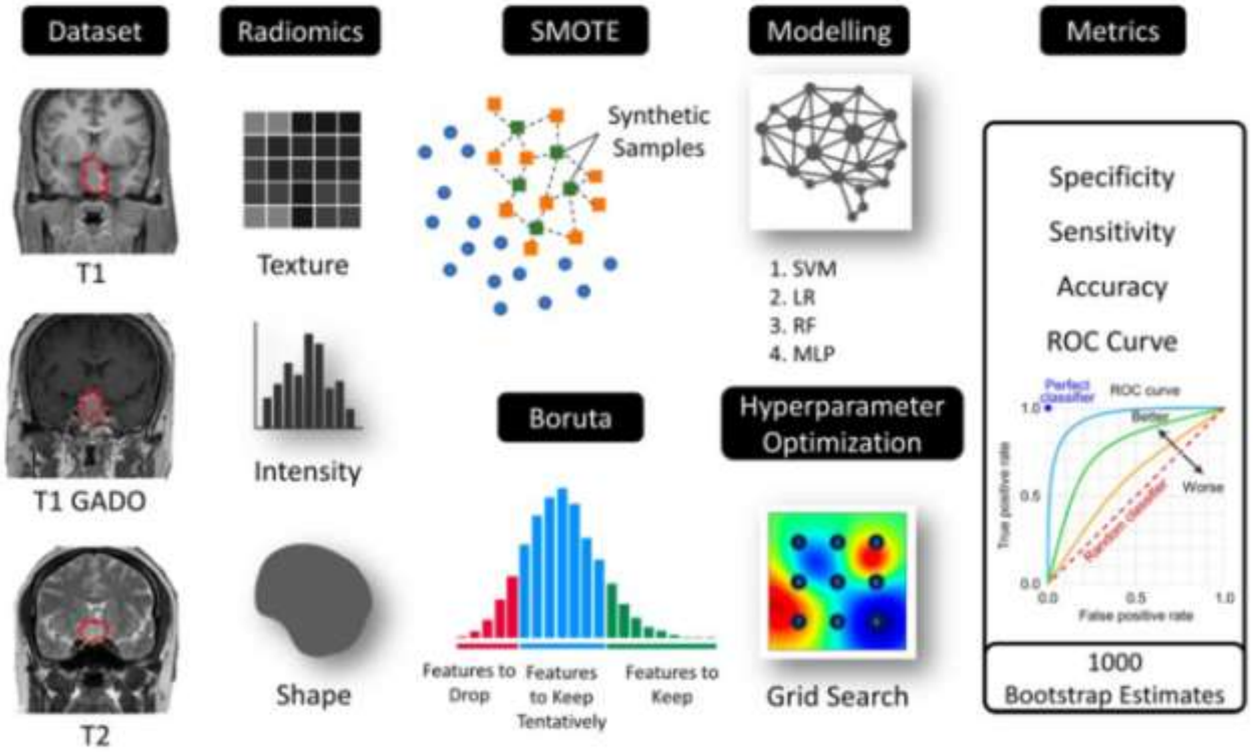
Radiomics in preoperative classification of PitNETs

Home > Acta Neurochirurgica > Article

Is radiomics a useful addition to magnetic resonance imaging in the preoperative classification of PitNETs?

Sathya A, Abhijit Goyal-Honavar, Ari G Chacko, Anitha Jasper, Geeta Chacko, Devadhas Devakumar, Joshua Anand Seelam, Balu Krishna Sasidharan, Simon P Pavamani & Hannah Mary T Thomas **2024 Feb**

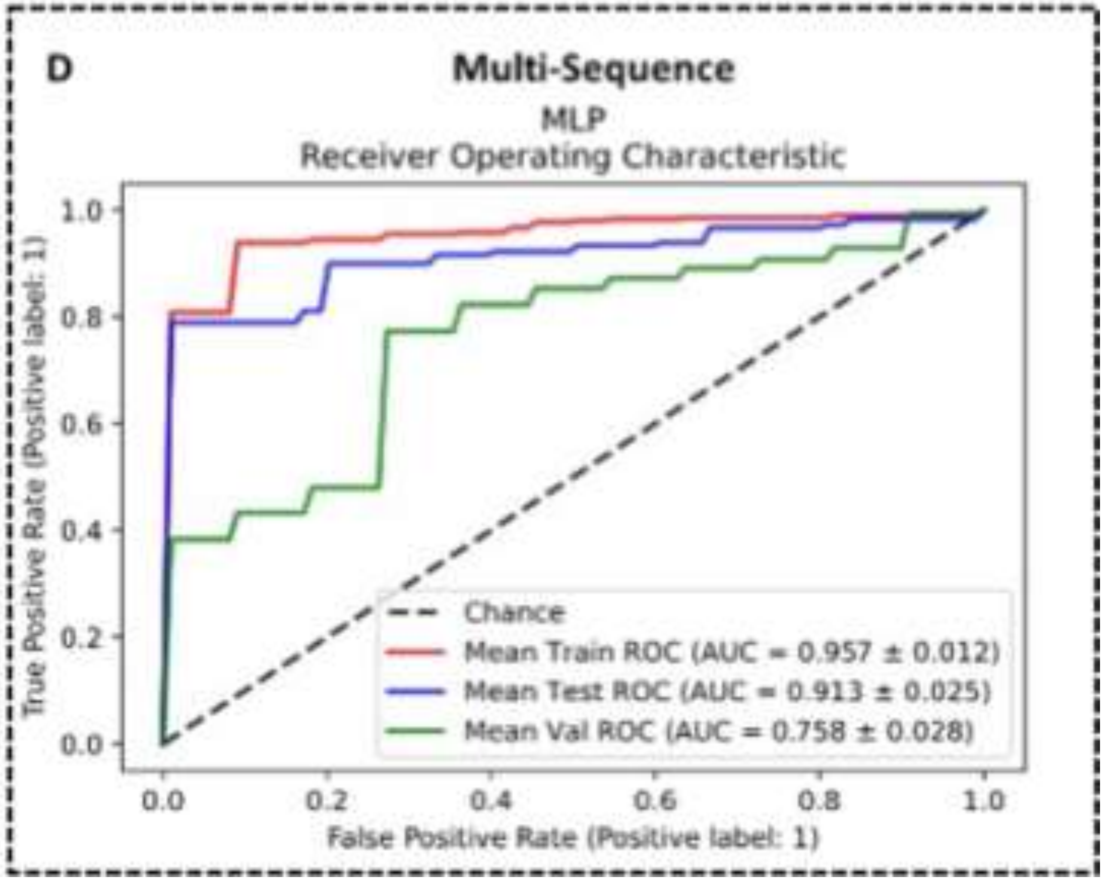




Radiomics in preoperative classification of PitNETs

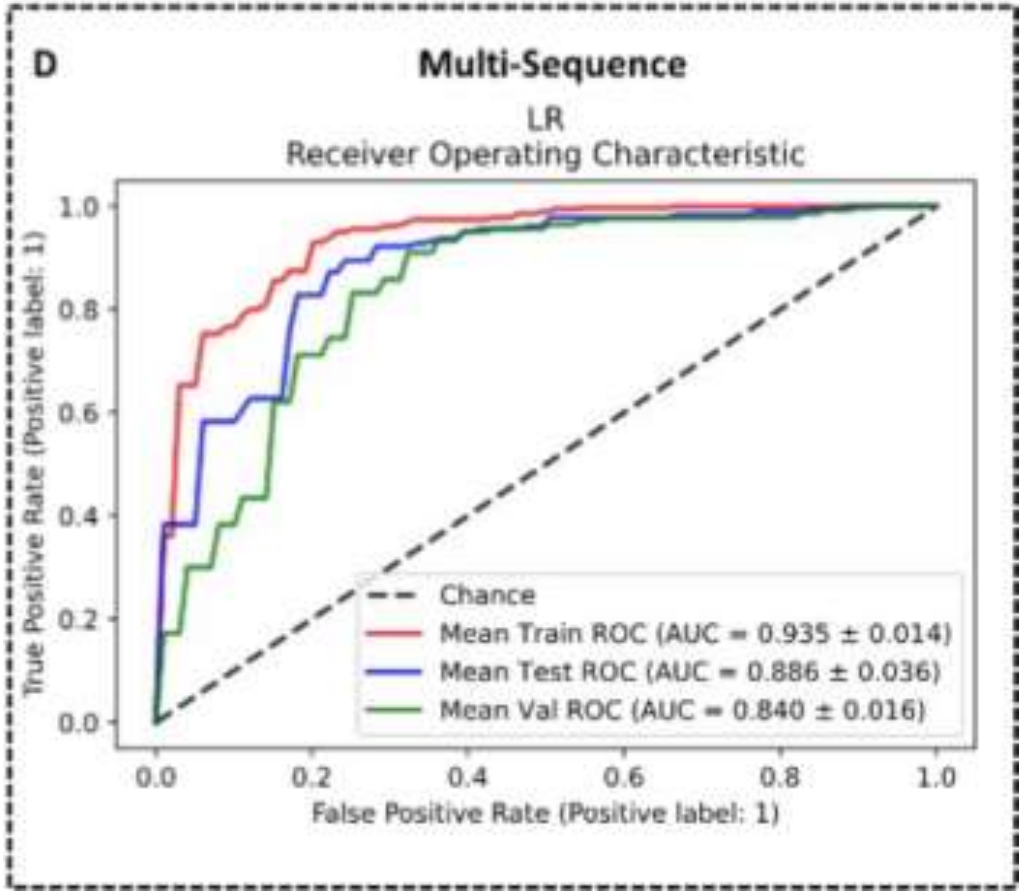
high- and low-risk non-functioning PitNETs

AUC	Accuracy	Sensitivity	Specificity
0.76	0.67	0.66	0.72



somatotroph and gonadotroph PitNETs

AUC	Accuracy	Sensitivity	Specificity
0.84	0.74	0.70	0.81



Sathya et al Acta Neurochirurgica 2024

Tata Memorial Hospital Projects

- Started in 2018 : Retrospective studies to explore its potential

- No of Radiomics based Research projects :17
  (across all cancers; 3 projects on brain tumors)

- Radiomics extraction software used: TexRAD ^{TM} & Pyradiomics

- Research projects with specific endpoints
  - Grading of Cancer
  - Molecular classification of disease
  - Response to Therapy
  - Survival Outcomes

- Publications : 5 & Abstract in conferences: 6

Radiomics & Deep Learning in molecular classification of cancers

Predicting IDH subtype of high Grade Astrocytoma and Glioblastoma from tumor radiomic patterns extracted from Multiparametric Magnetic Resonance Images

frontiers

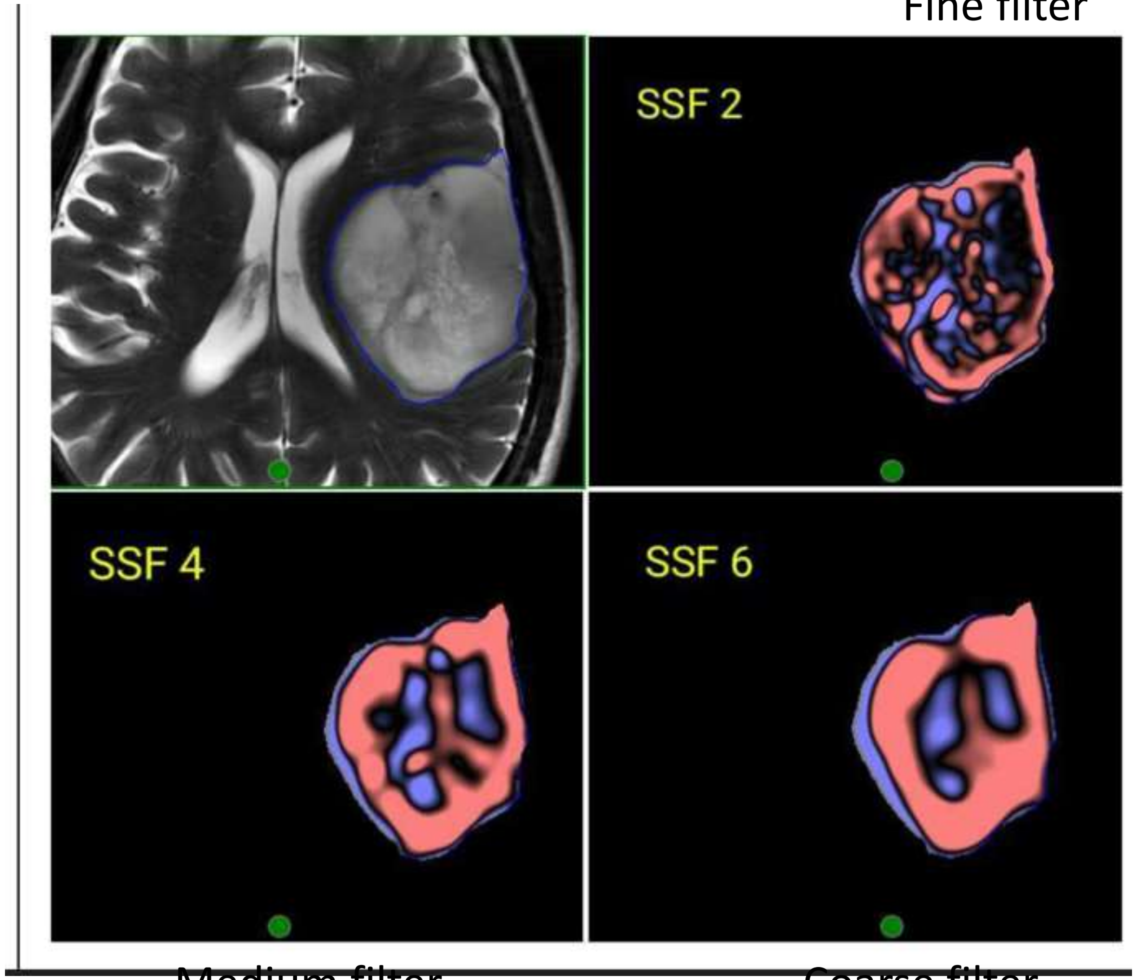
Predicting IDH subtype of Grade 4 Astrocytoma and Glioblastoma from tumor radiomic patterns extracted from Multiparametric Magnetic Resonance Images using a machine learning approach.

Pashmina Kandalgaonkar[1], Ann C. Saju[1], Arpita Sahu[1*], Abhishek Mahajan[1], Meenakshi Thakur[1], Sridhar Epari[1], Ayushi Sahay[1], Prakash Shetty[1], Ali A. Moiyadi[1], Jai Prakash Agarwal[1], Tejpal Gupta[1], Jayant Goda[1]

Kandalgaonkar & Ann Christy Saju et al
Frontiers in Oncology, 2022

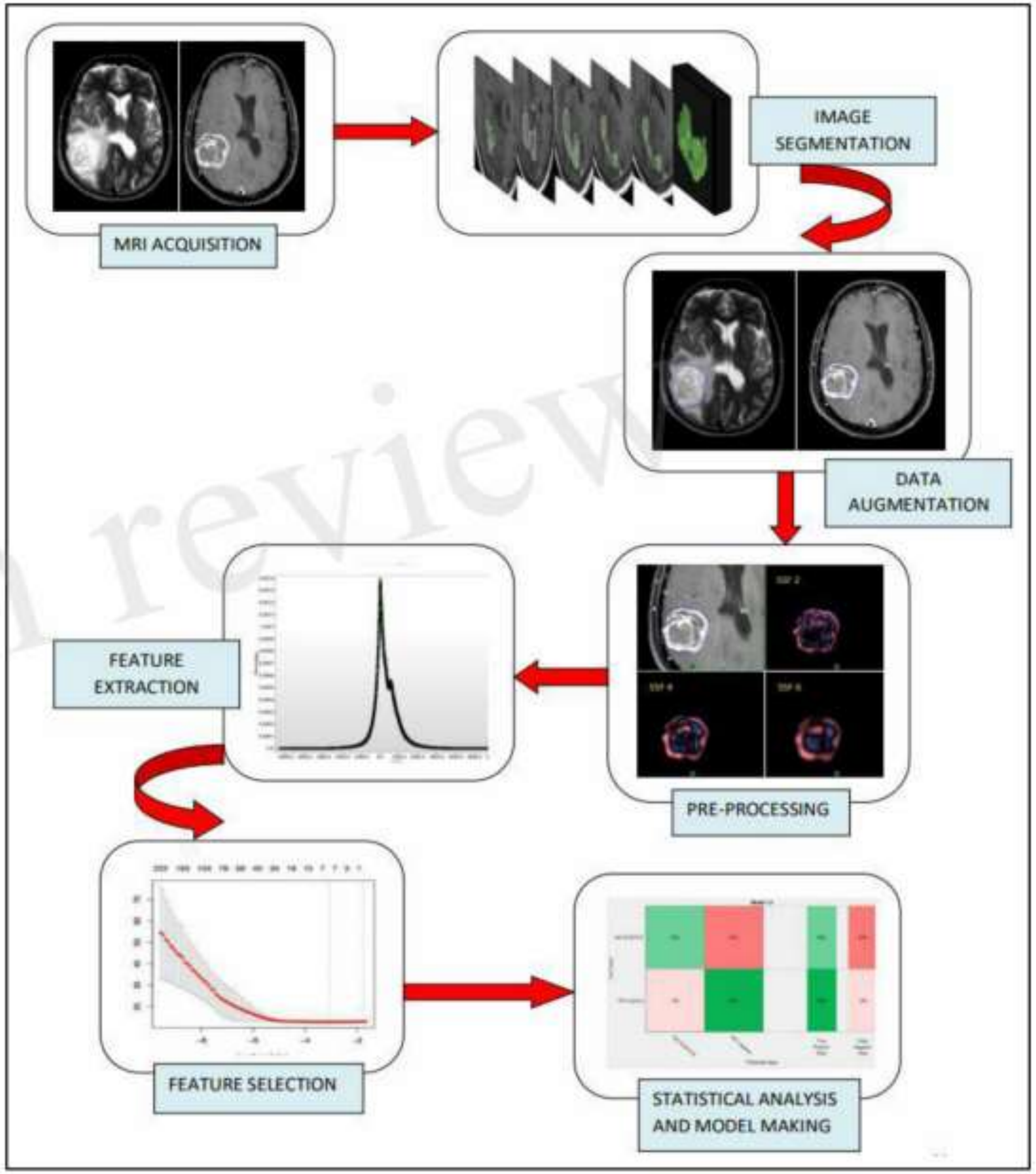
- N= 100 pts
- Imaging protocol T1+C & T2W MRI sequences
- 82 texture features each in T1W+C &T2W images

Fine filter



Medium filter

Coarse filter

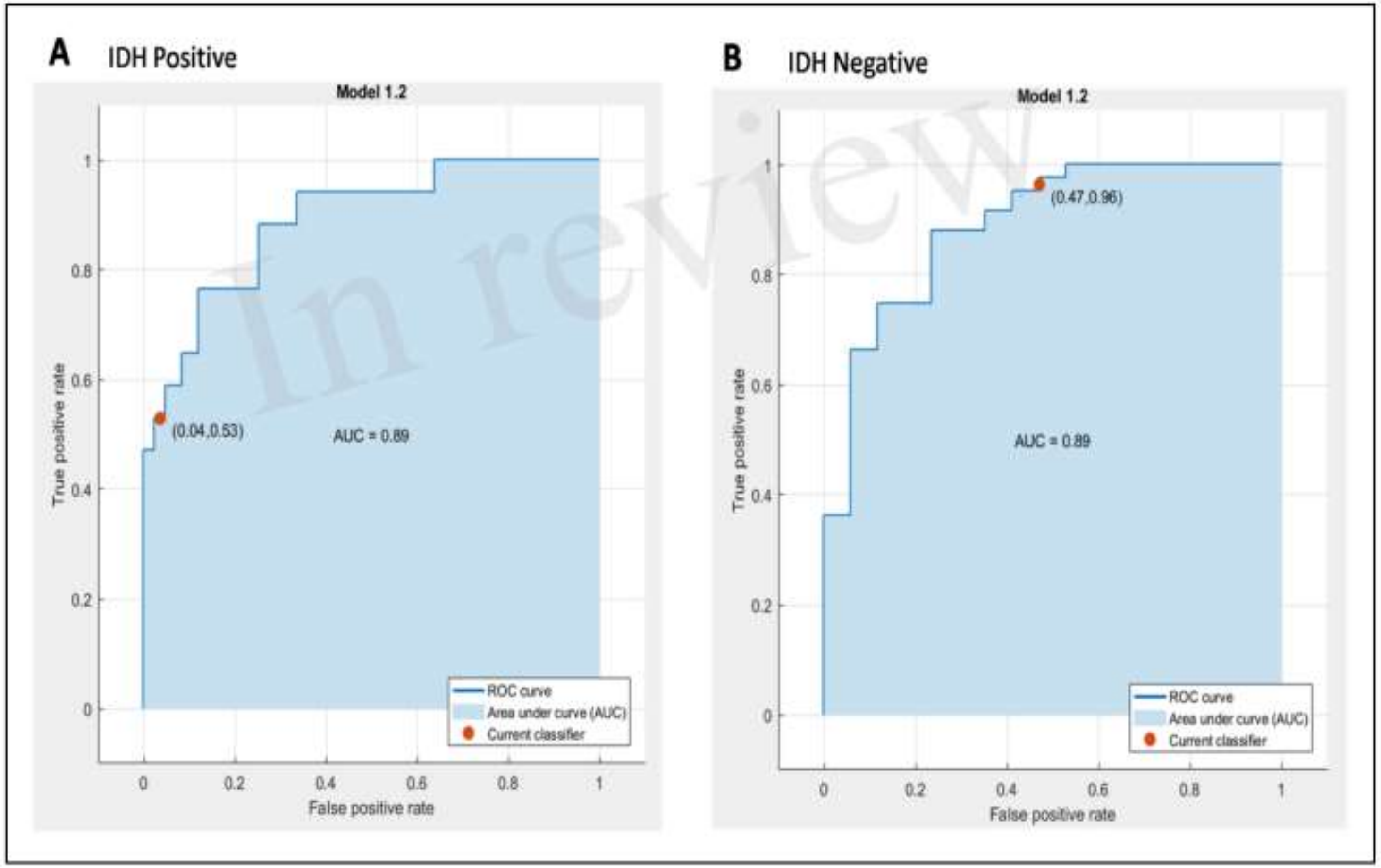


LASSO selected features used for model development

T1W+C TEXTURE FEATURES (N = 7)	T2W TEXTURE FEATURES (N = 7)
KURTOSIS_0_T1C	MEAN_0_T2
ENTROPY_2_T1C	MPP_0_T2
KURTOSIS_2_T1C	KURTOSIS_0_T2
MEAN_5_T1C	MEAN_4_T2
KURTOSIS_5_T1C	GLCM1_clusterShade_T2
SKEWNESS_6_T1C	GLCM1_idn_T2
GLCM4_correlation_T1C	GLCM1_sumEntropy_T2

Performance of best classification model

ROC curves of the best model for prediction of the two molecular subgroups using combined multi-slice T1+C and T2w GLCM features using Quadratic SVM, (A) IDH positive and (B) IDH negative



Best Model(4 GLCM+10 first order features)

Diagnostic metrics	IDH –VE (n=83)	IDH +VE (n=17)
AUC	**0.89**	**0.89**
Sensitivity	96%	53%
Specificity	52.9%	96.4%
FNR	4%	47%
PPV	90.9%	75%
NPV	75%	90.9%
Overall Accuracy	**89%**	

10-fold internal cross validation

MEdulloblastoma **R**adiomics as a **M**olecular **A**djunct **I**n **D**iagnosis (**MERMAID**)- **Initial Analysis**

BJR

https://doi.org/10.1259/bjr.20211359

Received: 08 December 2021 | Revised: 16 February 2022 | Accepted: 04 March 2022 | Published online: 21 March 2022

Cite this article as:
Saju AC, Chatterjee A, Sahu A, Gupta T, Krishnatry R, Mokal S, et al. Machine-learning approach to predict molecular subgroups of medulloblastoma using multiparametric MRI-based tumor radiomics. *Br J Radiol* (2022) 10.1259/bjr.20211359

FULL PAPER

Machine-learning approach to predict molecular subgroups of medulloblastoma using multiparametric MRI-based tumor radiomics

[1]ANN CHRISTY SAJU, MD, [1]ABHISHEK CHATTERJEE, MD, [2]ARPITA SAHU, MD, [1]TEJPAL GUPTA, MD,DNB, [1]RAHUL KRISHNATRY, MD, [3]SMRUTI MOKAL, MSc, [4]AYUSHI SAHAY, MD, [4]SRIDHAR EPARI, MD, [5]MAYA PRASAD, MD, [5]GIRISH CHINNASWAMY, MD, [1]JAI PRAKASH AGARWAL, MD and [1,6]JAYANT S GODA, MD,DNB

Ann Christy Saju et al, British Journal of radiology 2020

2007- 2019

Patients Screened-N=221

Patients excluded-N=183

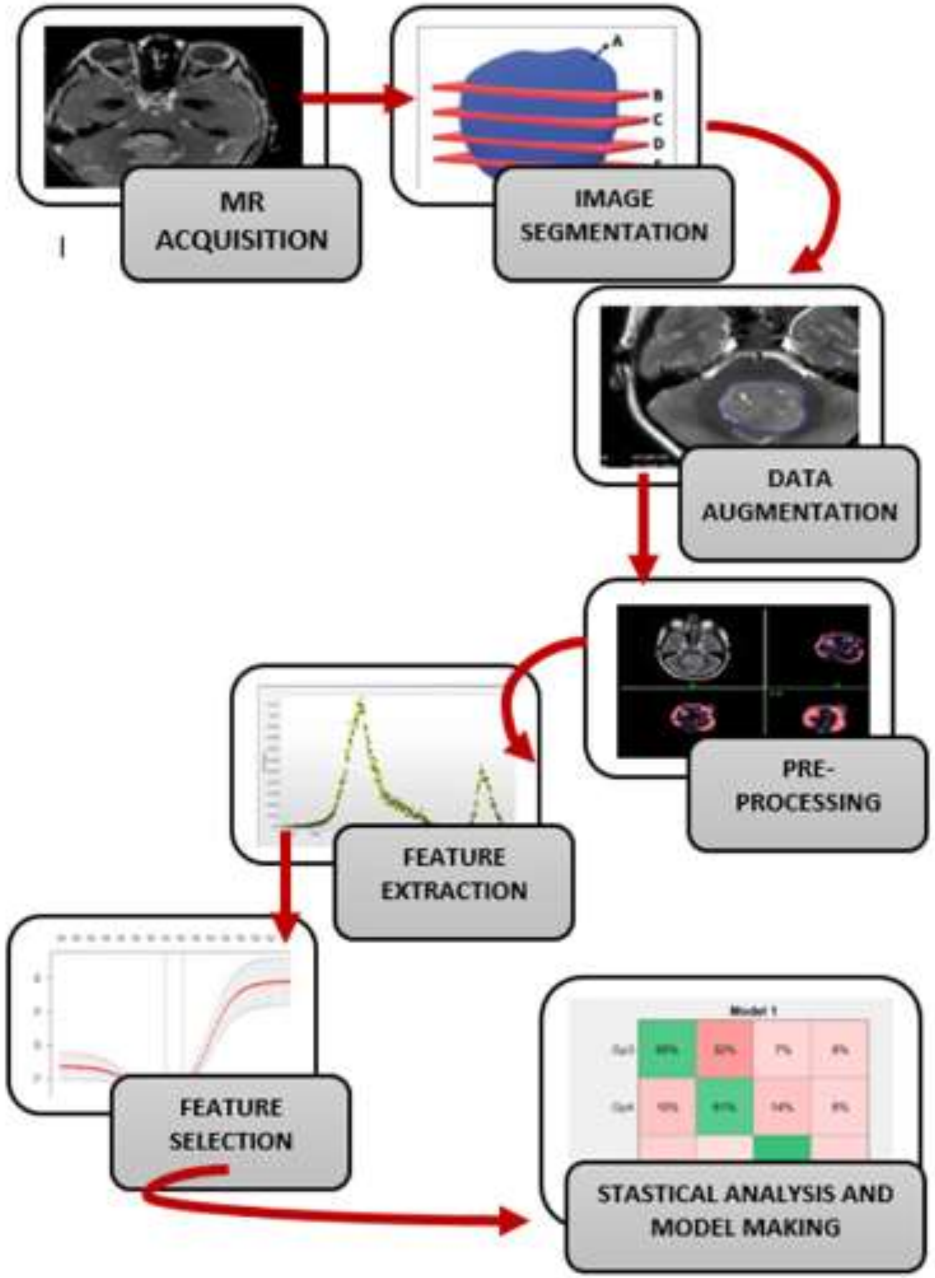
- 8 Patients due to Non-availability of Molecular sub-group.
- 2 Patients were unclassifiable/inconclusive on Molecular sub-grouping
- 173 patients did not have MRI in DICOM format.

Eligible patients- N=38

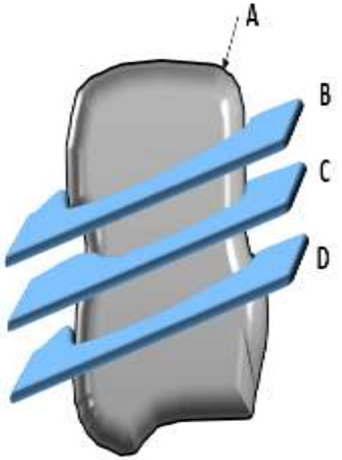
Single Slice analysis with Data Augmentation (Texture only) N=38 patients

Volumetric Analysis (Texture + Semantics) N=38 patients

No. of T1w+C slices N=174
No. of T2w slices N=170



Radiomics Work flow



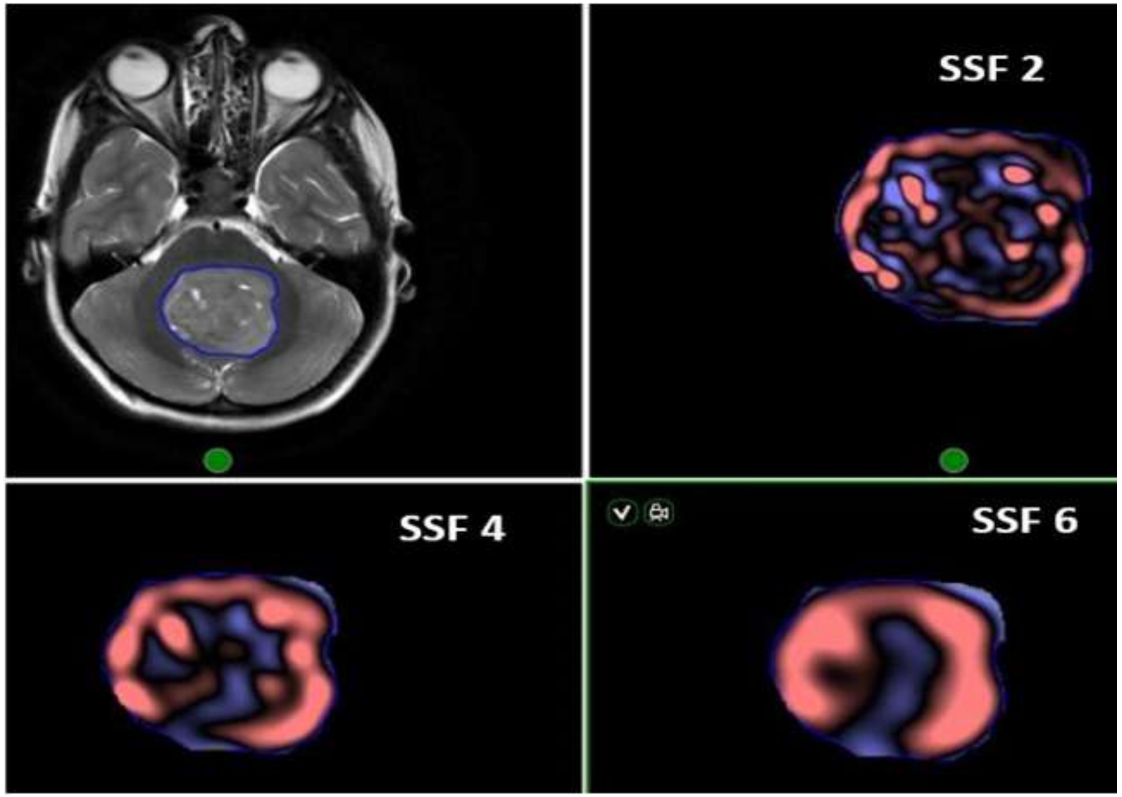
Data Augmentation

Single slice multiple sampling of volumes

T1+C -174,T2W-170

T1w+C & T2W:164 texture features

Fine filter



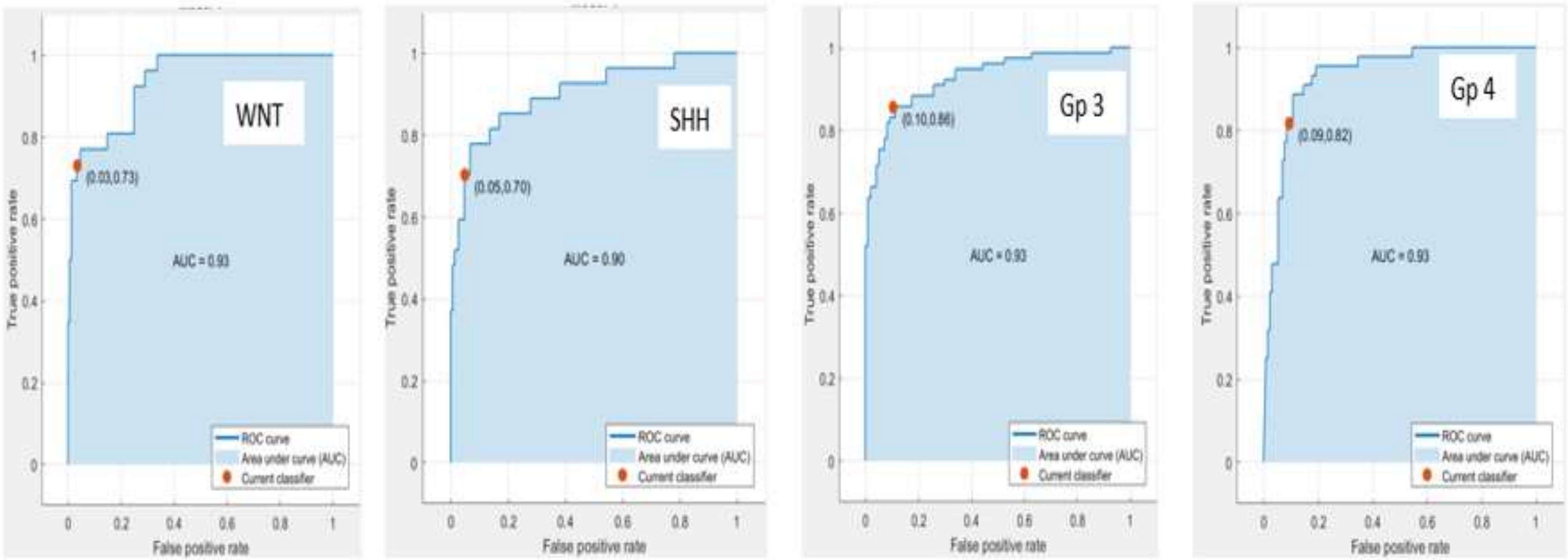
Medium filter

Coarse filter

Texture Features Extracted	
First-Order Features	Mean
	Standard Deviation
	Mean of Positive pixels
	Entropy
	Skewness
	Kurtosis
GLCM features	Autocorrelation
	Cluster prominence
	Cluster shade
	Cluster tendency
	Contrast
	Correlation
	Dissimilarity
	Homogeneity
	Joint average
	Joint energy
	Joint entropy
	Idm (inverse difference moment)
	Difference entropy
	Difference variance
	Idmn (inverse difference moment normalized)
	Idn (inverse difference normalized)
	Inverse variance
	Sum entropy
	Sum squares
	Joint maximum
Shape/topographic features	Perimeter
	Area
	Elongation
	Sphericity
	Long axis
	Short axis

Performance of Single slice Multiple Sampling approach using GLCM + shape features in T1w images

T1 –glcm+topo-Accuracy- 80.5% (One Vs One Multiclass method)



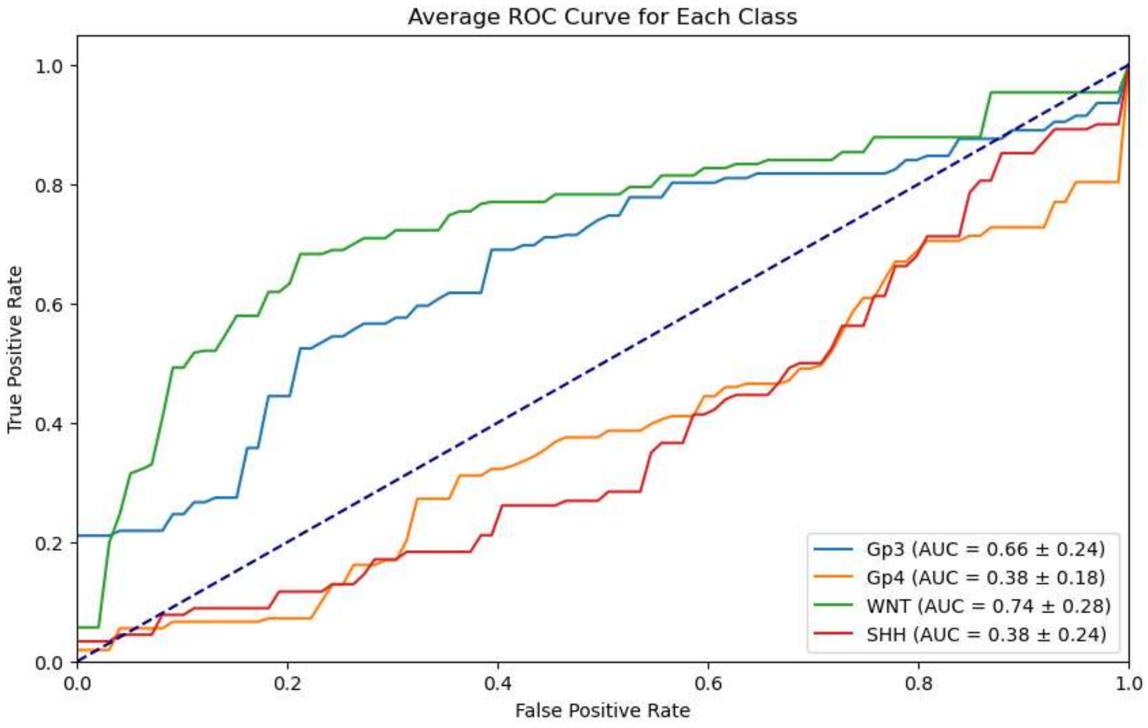
Support vector Classification

	WNT	SHH	Group3	Group4
AUC	0.93	0.9	0.93	0.93
Sensitivity	73%	70%	86%	82%
PPV	79%	73%	87%	75%
False discovery Rate	21%	27%	25%	13%

Best Model(30 GLCM+6 shape features)

Validation cohort (N= 30)

Support vector Classification



	Precision	Recall	F1 Score	Sensitivity	Specificity
Gp3	38.27	26.94	30.05	NaN	84.11
Gp4	58.07	26.60	34.82	58.07	86.58
WNT	28.22	50.00	34.05	NaN	75.11
SHH	26.95	58.61	33.83	26.95	69.04

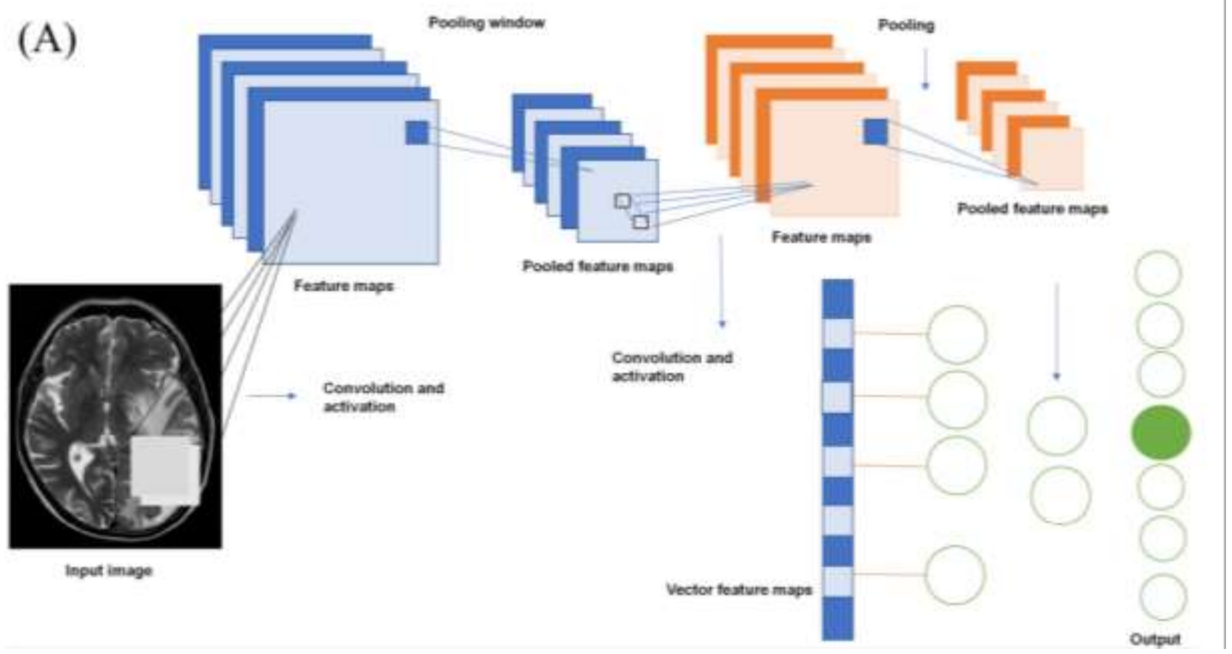
Exploration of Targeted Anti-tumor Therapy
Open Exploration

Open Access Original Article

Deep learning based automated epidermal growth factor receptor and anaplastic lymphoma kinase status prediction of brain metastasis in non-small cell lung cancer

Abhishek Mahajan[1,2*], Gurukrishna B[2], Shweta Wadhwa[2], Ujjwal Agarwal[2], Ujjwal Baid[3], Sanjay Talbar[3], Amit Kumar Janu[2], Vijay Patil[4], Vanita Noronha[4], Naveen Mummudi[5], Anil Tibdewal[5], JP Agarwal[5], Subash Yadav[6], Rajiv Kumar Kaushal[6], Ameya Puranik[7], Nilendu Purandare[7], Kumar Prabhash[4]

- N=117
- EGFR mutation: 33;ALK mutation:43; double negative:41
- Data was divided into 80% training and 20% testing
- Training was done using CNN architecture
- Different Deep learning algorithms were used

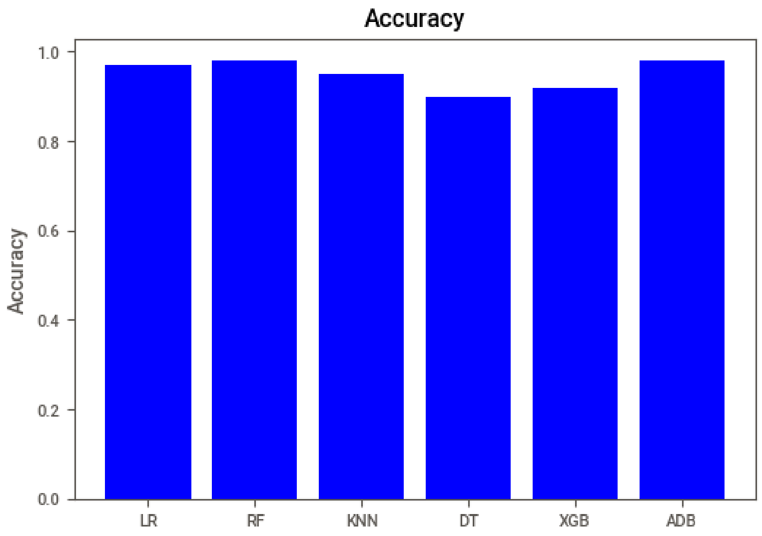


DL for predicting ALK & EGFR mutations in brain mets of lung cancer pts

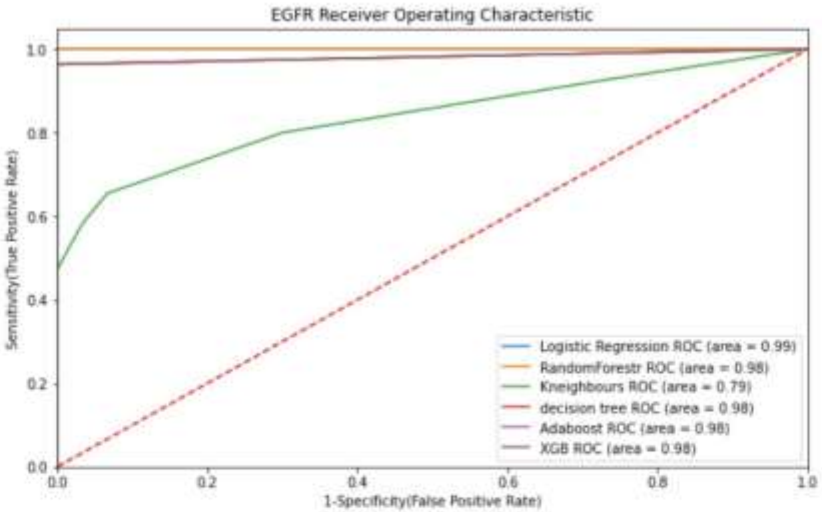
Architecture name	Accuracy without segmentation	Accuracy post segmentation
ResNet18	0.52	0.62
ResNet34	0.56	0.65
ResNet50	0.61	0.66
MobileNetV1	0.60	0.66
MobileNetV2	0.62	0.69
Xception	0.74	0.83
EfficientNetB0	0.76	0.89

Predicting Biomarker using Imaging Biomarker

- 282 NSCLC patient’s pre-treatment CT scans
- [EGFR+(178)/ EGFR- (104)]
- 108 stable radiomic features (based on our earlier stability study (Jha A,K, etal,2021)
- hierarchical clustering
- RFE : 6 radiomic features
- ML algorithms: Decision tree , Random forest, K-nearest neighbor, XG-boost, Adaboost and Logistic regression.
- Train and Test(70:30)
- Models were compared based on Accuracy and AUC in the Test set



LR= Logistic regression, RF= Random forest, KNN=K-nearest neighbor , DT=Decision tree, XGB=XG-boost, ADB=Adaboost



Accessing the predictability of Epidermal growth factor receptor status from Computed Tomography radiomics using machine learning.

Sherkhane, U., Jha, A. K., Jaiswar, V., Mithun, S., Rangarajan, V., Wee, L., & Dekker, A. (2022, September). *EUROPEAN JOURNAL OF NUCLEAR MEDICINE AND MOLECULAR IMAGING* (Vol. 49, No. SUPPL 1, pp. S623-S623).

Radiomics in Grading of Cancer

Machine learning based Radiomics for Classifying Glioma grade from Magnetic Resonance Images of the brain

- N= 83
- Histopathologically proven gliomas
- underwent T2W sequence MRI

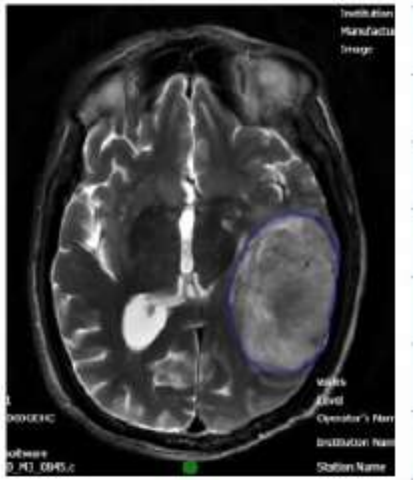
- **LASSO regression method** was selected for feature reduction

    -The features selected were 3 first order and 1 shape feature to develop the model

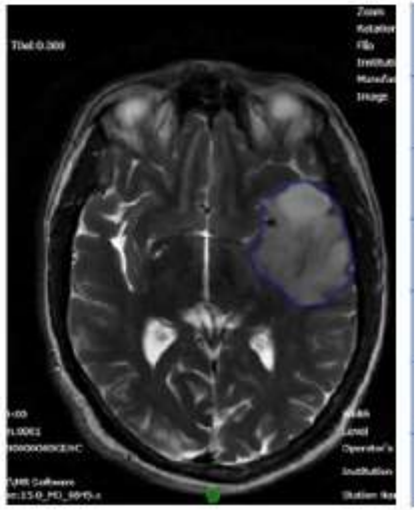
- **Used multiple machine learning tools**

    - Gradient boost classifier
    - Adaboost classifier
    - Random Forest classifier
    - Support vector machine Classifier
    - Naïve Bayes Classifier

HGG



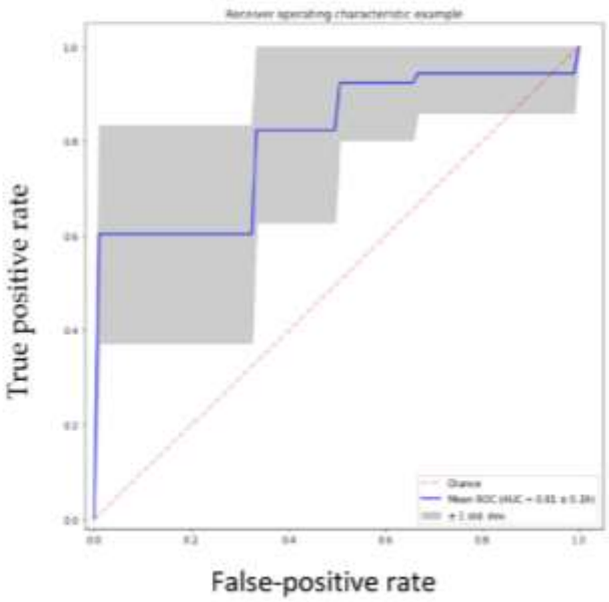
LGG



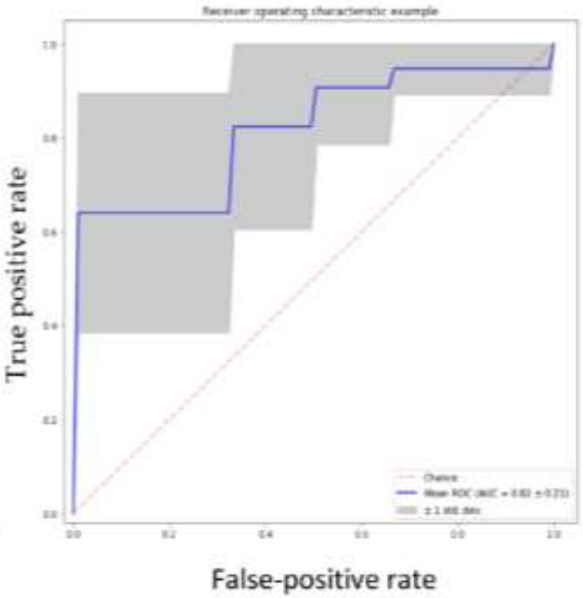
Kumar A et al; Journal of personalized medicine 2023

Radiomics for Classifying Glioma Grade

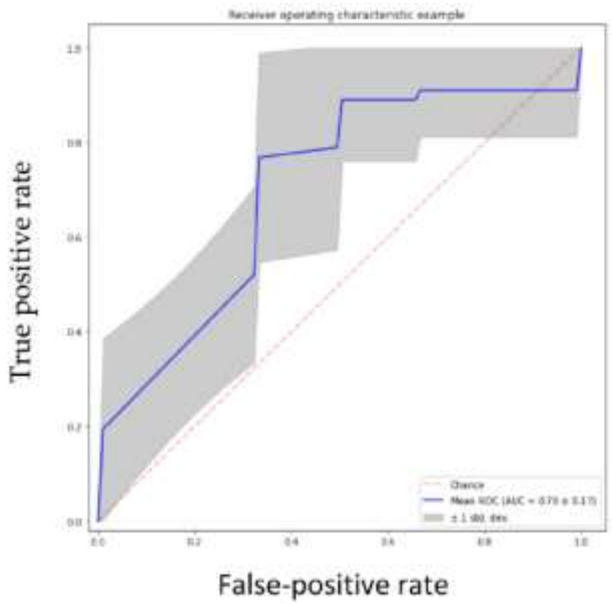
Random forest classifier



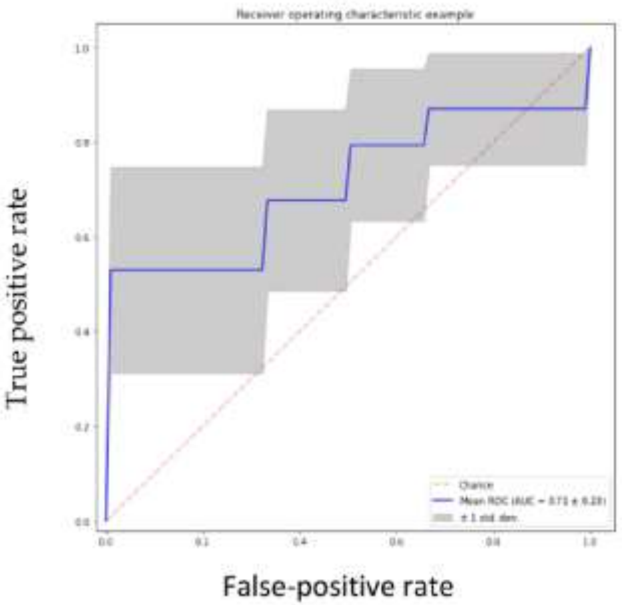
Support Vector classifier



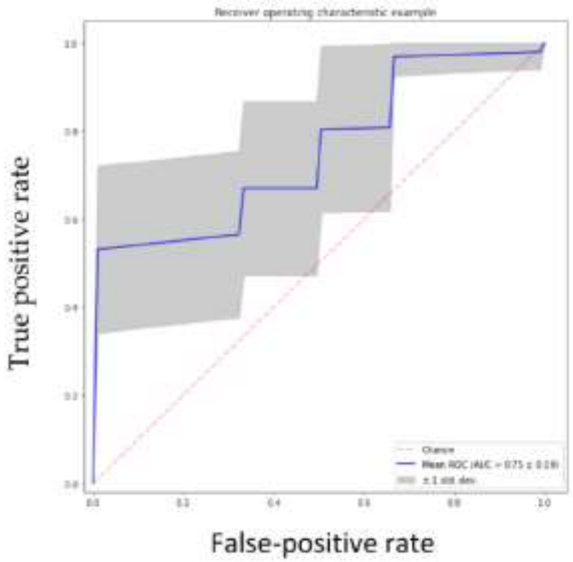
Gradient boosting Classifier



Naive Bayes classifier



AdaBoost
classifier (ABC)



Kumar A et al; Journal of personalized medicine 2023

Prediction model performance from selected radiomics features for classifying LGG from HGG.

Algorithm/ Model	Validation	Class Probability			Performance Metrics			
		0 Low-Grade (Grade-2/3)	1 High-Grade (Grade 4 Astrocytoma)	Accuracy	The Area under the Curve (AUC)	Precision	Recall	F1 Score
Random Forest Classifier	10-fold cross validation	0.80	0.90	0.83 ± 0.16	0.81 ± 0.19	0.85 ± 0.13	0.93 ± 0.12	0.88 ± 0.11
Support vector Machine Classifier	10-fold cross validation	0.62	0.79	0.82 ± 0.14	0.82 ± 0.21	0.85 ± 0.13	0.91 ± 0.10	0.87 ± 0.09
Gradient boost Classifier	10-fold cross validation	0.96	0.98	0.71 ± 0.09	0.70 ± 0.17	0.80 ± 0.10	0.79 ± 0.13	0.78 ± 0.08
Naïve Bayes Classifier	10-fold cross validation	0.58	0.72	0.66 ± 0.18	0.71 ± 0.23	0.78 ± 0.06	0.72 ± 0.17	0.73 ± 0.14
Ada boost Classifier	10-fold cross validation	0.57	0.74	0.74 ± 0.19	0.75 ± 0.19	0.76 ± 0.09	0.79 ± 0.19	0.73 ± 0.13

- **Random forest model was found to be a better** than the other three classifier models for all the performance metrics in differentiating the grades of gliomas.

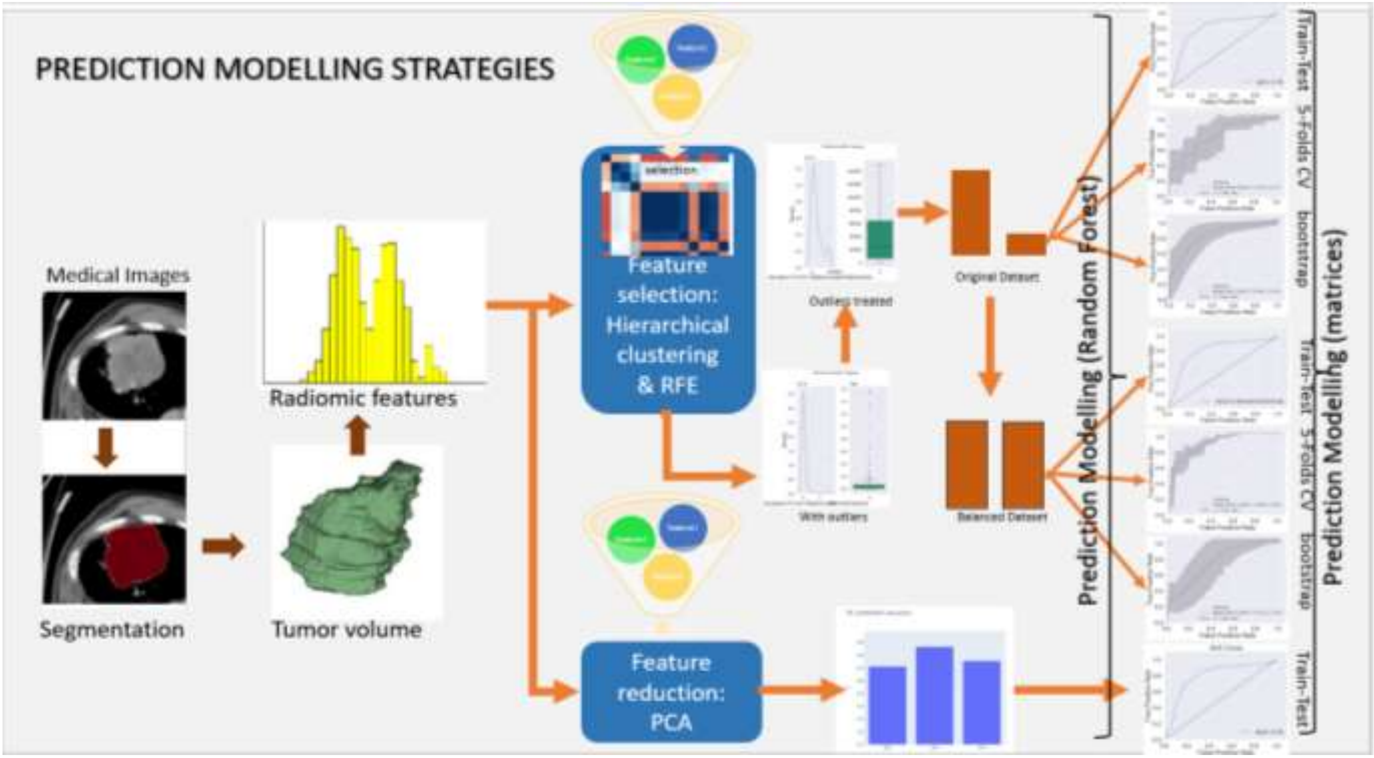
- The RF classifier on glioma grades achieved a predictive performance **(AUC:0.81, accuracy :0.83, precision :0.85 ,Recall:0.93 & F1 score:0.88)**

Kumar A et al; Journal of personalized medicine 2023

Characterization of lesions

Characterization of SPN using Radiomic feature

- Total 163 patients 117 metastatic and 46 benign .
- Feature selection by RFE: 5 radiomic features
- PCA: 3 principal components
- Data balancing: SMOTE
- Prediction model: Random forest
- Validation: test, cross-validation and bootstrap.
- Accuracy: 0.8, 0.80±0.07, and 0.84±1.11 (original)
- Accuracy: 0.8, 0.83±1.10, and 0.80±0.07 (balanced)
- PCA accuracy: 0.86.



Artificial Intelligence assisted PET imaging biomarker for the Characterization of Solitary Pulmonary Lesions

Ashish Kumar Jha, Sneha Mithun, Umesh Kumar Baburao Sherkhane, Akhilesh Tripathi, Grace Monica S. Mehta, Nilendu Purandare, Leonard Wee, V. Rangarajan, Andre Dekker, Molecular Imaging and Biology

Treatment response and prognostication

MRI based radiomics as an Imaging biomarker for locally advanced carcinoma rectum: Predicting tumor response, and survival following Neoadjuvant Chemoradiotherapy.

Screened 614 pts

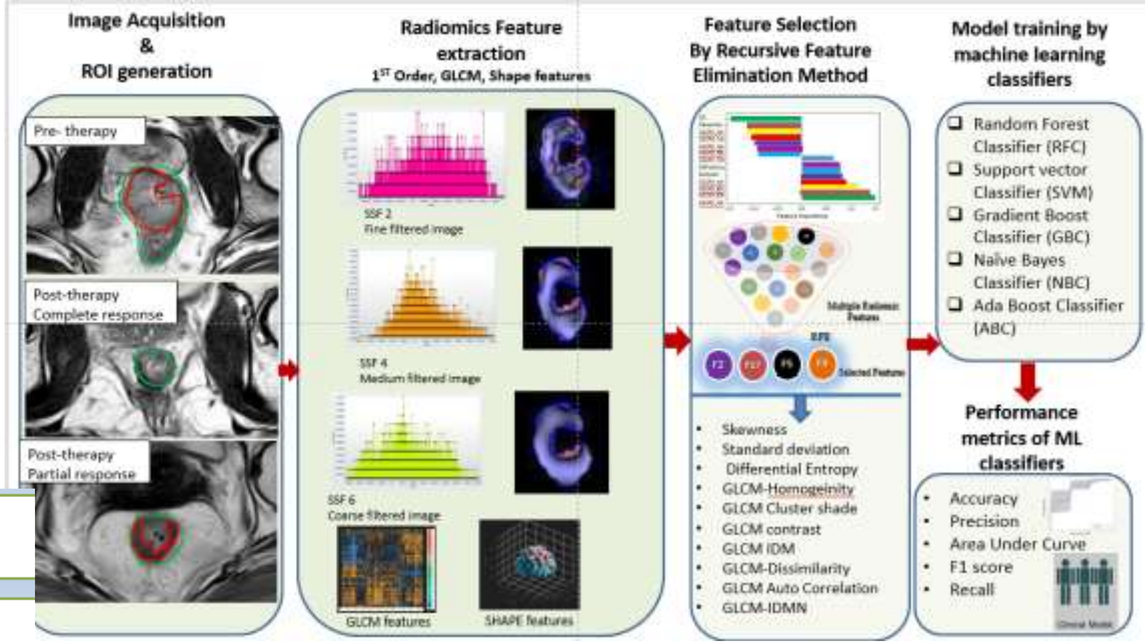
Analysed 100 pts

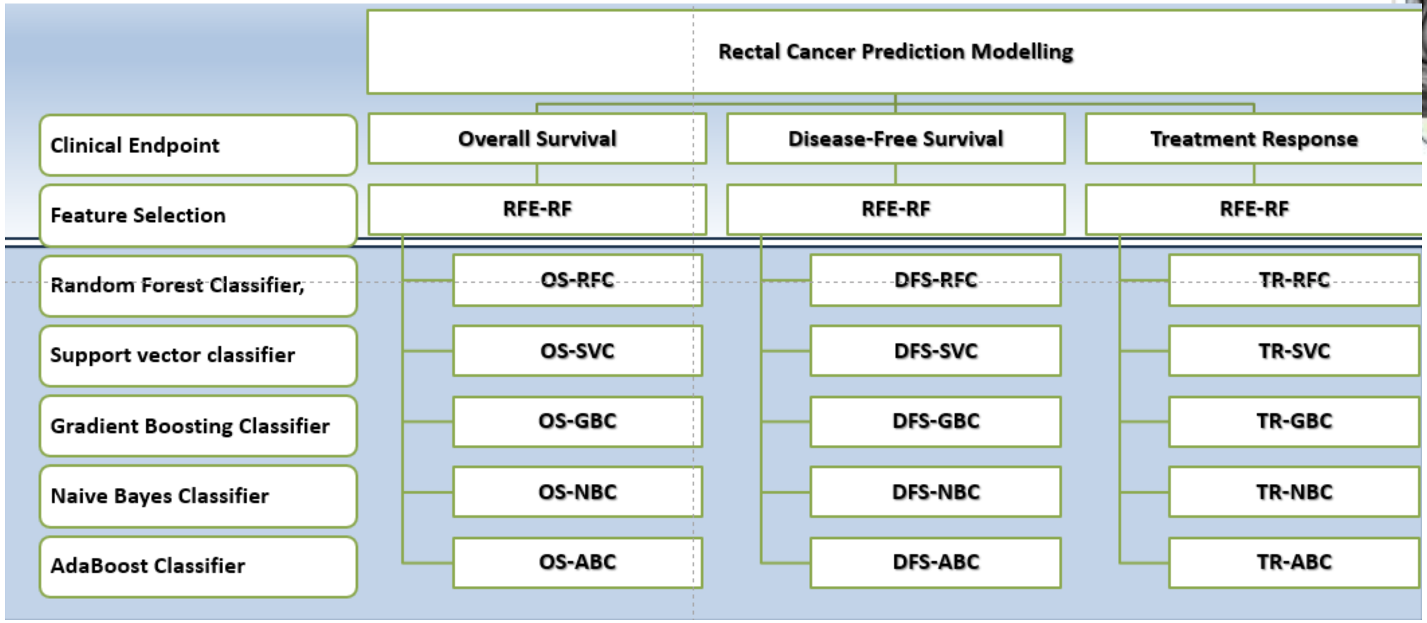
No of radiomic features :62

End points : Tumor response to NACTRT

2 yr DFS

3 Yr OS





Clinical endpoint Criteria	Feature Selection method	Selected optimal radiomic features from Baseline and Post – Operative MRI
Tumor response to NACTRT	Recursive feature elimination using random forest algorithm	Standard deviation (SSF3)- Baseline MRI Standard deviation (SSF2)- Baseline MRI Skewness(SSF2)- Baseline MRI GLCM-IDMN- Post-NACTRT MRI Differential Entropy- NACTRT MRI
3- year Overall survival	Recursive feature elimination using random forest algorithm	Skewness (SSF4)- Baseline MRI Skewness (SSF5)- Baseline MRI GLCM-Homogeinity- Baseline MRI GLCM-Contrast – Baseline MRI GLCM-Dissimilarity- Baseline MRI GLCM-IDM- Baseline MRI
2- year disease-free survival (DFS)	Recursive feature elimination using random forest algorithm	GLCM Cluster shade- Baseline MRI 'GLCM homogeneity- Baseline MRI GLCM IDM- Baseline MRI GLCM Auto Correlation- Post- NACTRT MRI, GLCM homogeneity- Post-NACTRT MRI

Prediction Model performance from selected radiomic features for classifying tumour response (Complete response v/s no or partial response)

Machine learning Algorithm	Cross-Validation	Accuracy	Classification Report			AUC
			Precision	Recall (sensitivity)	f1-score	
Random Forest Classifier (RFC)	10-folds	0.72±0.12	0.77±0.10	0.87±0.11	0.81±0.07	0.79±0.15
Support vector classifier (SVC)	10-folds	0.68±0.16	0.73±0.11	0.87±0.14	0.79±0.11	0.69±0.16
Gradient Boosting Classifier (GBC)	10-folds	0.67±0.13	0.75±0.08	0.77±0.16	0.75±0.11	0.68±0.21
Naive Bayes Classifier(NBC)	10-folds	0.67±0.06	0.61±0.06	0.99±0.04	0.80±0.04	0.62±0.20
AdaBoost Classifier (ABC)	10-folds	0.71±0.12	0.79±0.12	0.84±0.14	0.80±0.08	0.73±0.23

Prediction Model performance from selected radiomic features for 2 year DFS

Machine learning Algorithm	Cross-Validation	Accuracy	Classification Report			AUC
			Precision	Recall (sensitivity)	f1-score	
Random Forest Classifier (RFC)	10-folds	0.73±0.17	0.74±0.20	0.75±0.19	0.73±0.18	0.75±0.21
Support vector classifier (SVC)	10-folds	0.58±0.18	0.58±0.16	0.76±0.24	0.65±0.17	0.68±0.19
Gradient Boosting Classifier (GBC)	10-folds	0.64±0.17	0.70±0.23	0.66±0.19	0.66±0.17	0.67±0.22
Naive Bayes Classifier(NBC)	10-folds	0.52±0.14	0.53±0.19	0.77±0.31	0.59±0.18	0.59±0.23
AdaBoost Classifier (ABC)	10-folds	0.63±0.21	0.63±0.22	0.65±0.28	0.62±0.24	0.65±0.26

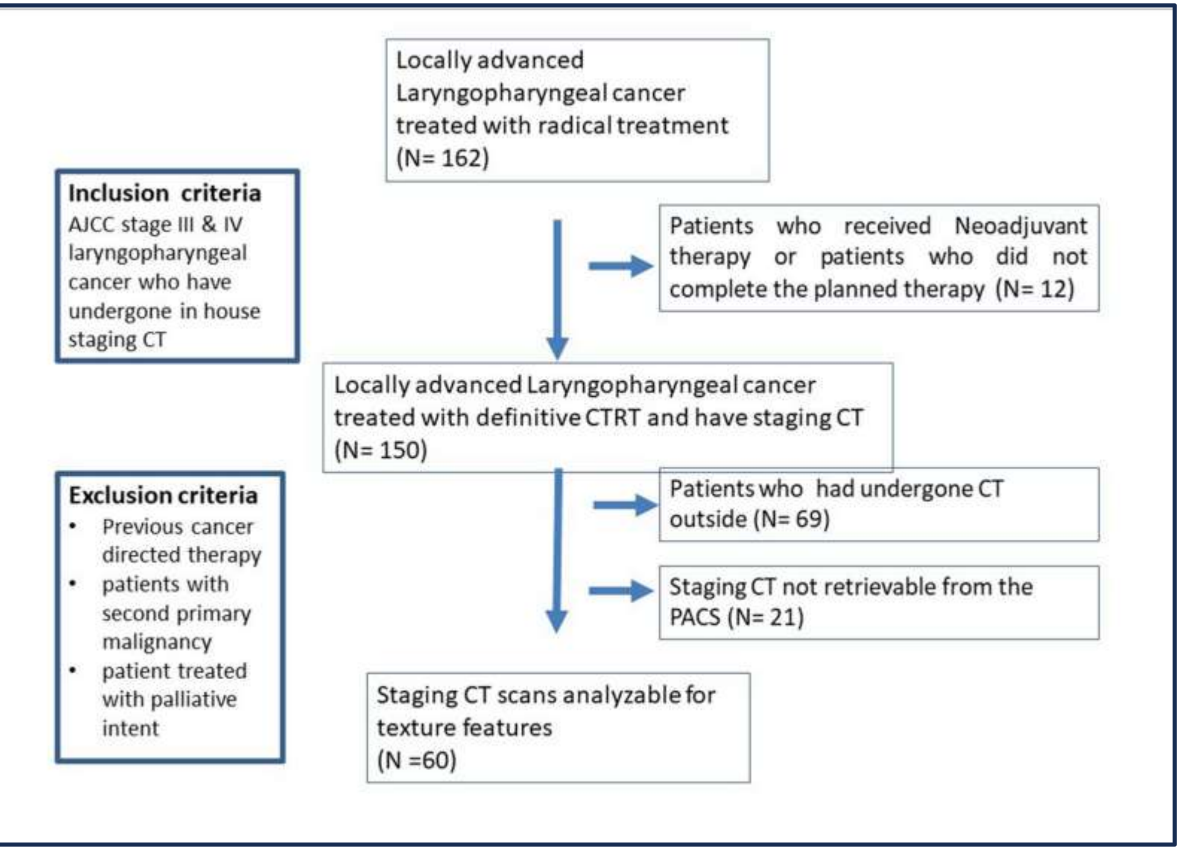
Prediction Model performance from selected radiomic features for Overall Survival at 3 years

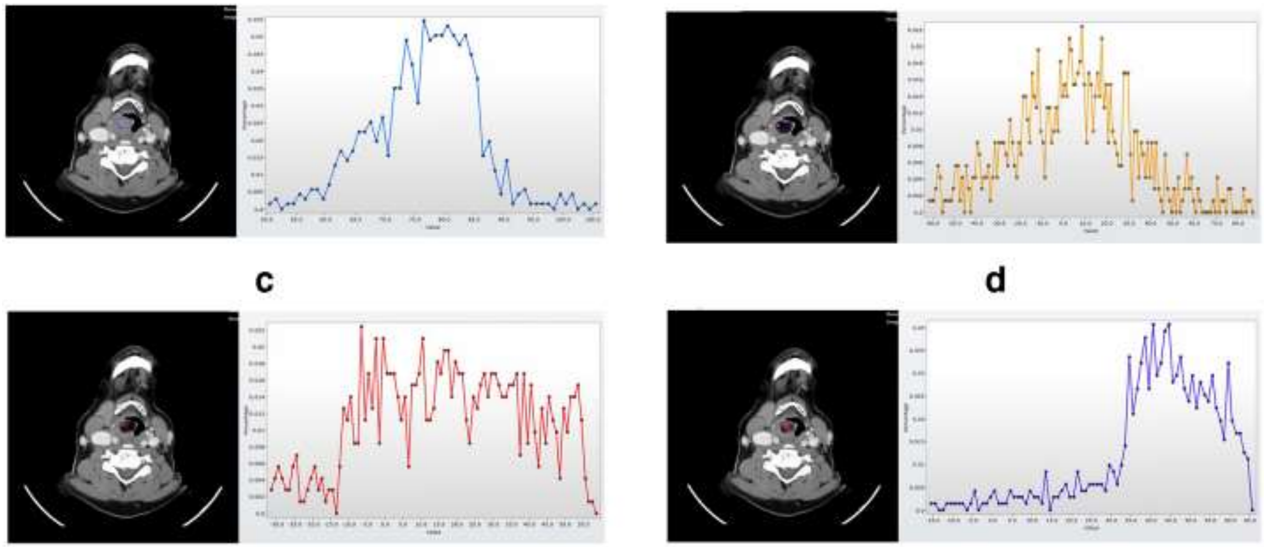
Machine learning Algorithm	Cross-Validation	Accuracy	Classification Report			AUC
			Precision	Recall (sensitivity)	f1-score	
Random Forest Classifier (RFC)	10-folds	0.80±0.09	0.81±0.08	0.89±0.07	0.85±0.04	0.77±0.08
Support vector classifier (SVC)	10-folds	0.73±0.13	0.76±0.10	0.91±0.12	0.82±0.08	0.70±0.21
Gradient Boosting Classifier (GBC)	10-folds	0.74±0.08	0.81±0.08	0.84±0.13	0.81±0.06	0.77±0.08
Naive Bayes Classifier(NBC)	10-folds	0.70±0.06	0.70±0.04	0.98±0.04	0.81±0.03	0.55±0.08
AdaBoost Classifier (ABC)	10-folds	0.66±0.12	0.79±0.08	0.89±0.09	0.83±0.05	0.70±0.21

Radiomics in organ preservation

Tumor radiomic features complement clinico-radiological factors in predicting long-term local control and laryngectomy free survival in locally advanced laryngo-pharyngeal cancers

[1]JAI PRAKASH AGARWAL, MD, [1]SHWETABH SINHA, MD, [1]JAYANT SASTRI GODA, MD, [1]KISHOR JOSHI, Dip RP, [1]RITESH MHATRE, Dip RP, [2]SADHANA KANNAN, MSc, [1]SARBANI GHOSH LASKAR, MD, [1]TEJPAL GUPTA, MD, [1]VEDANG MURTHY, MD, ASHWINI BUDRUKKAR, MD, [1]NAVEEN MUMMUDI, MD and [3]BALAJI GANESHAN, PhD





TeXRad Software

1st order intensity based histogram features

used spatial scaled filters to reduce the background noise

Parameters	**Local control**			**Laryngectomy free survival**		
	HR	95% CI	*p*-value	HR	95% CI	*p*-value
Age (years)	0.992	0.970–1.014	0.461	0.976	0.941–1.012	0.185
T stage T1,T2 *vs* T3,T4	0.629	0.333–1.189	0.154	0.468	0.19–1.151	0.098
AJCC Stage IV *vs* III	1.158	0.649–2.067	0.619	0.942	0.418–2.123	0.886
Subsite Hypopharynx *vs* larynx	1.120	0.624–2.010	0.704	0.547	0.246–1.220	0.141
Entropy (medium filter)	1.800	1.257–2.578	**0.001**	5.982	2.590–13.813	**0.0003**
MPP (medium Filter)	0.998	0.989–1.007	0.723	0.969	0.949–0.988	0.002

The Next Steps in TMH

- Prospective validation on an external data set to have more robust and interpretable results
- Need more concerted efforts in developing large and annotated imaging data bases through multicentric approach
- Planning to use Radiotherapy image data sets (CBCT & MVCT) images.
- Dosiomics : extracting features from radiation dose maps to study the end point of interest
  - Clinical outcomes
  - Radiation Toxicity

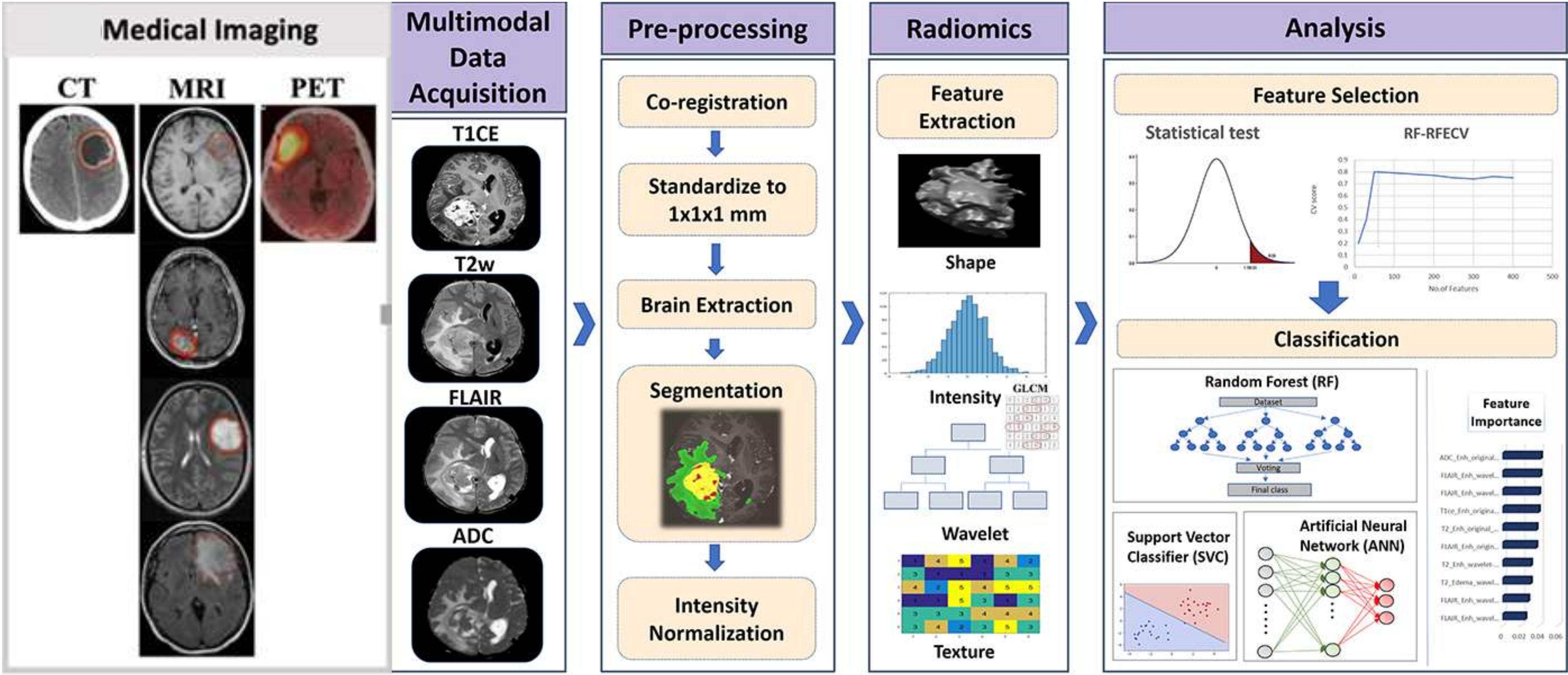
Is it prime time for AI or Radiomics to be used in clinical settings ?

Acknowledgements

- Professor JP Agarwal
- Dr Abhishek Chatterjee
- Dr Shwetabh Sinha
- Dr Arpita Sahu
- Dr Ashish Jha
- Dr Reena Engineer

Thank You!

Radiomics Workflow



Classifying PCNSL from GBM by DL/ ML approach

frontiers in Oncology

Front Oncol. 2022; 12: 884173.
Published online 2022 Oct 3. doi: 10.3389/fonc.2022.884173
PMCID: PMC9574102
PMID: 36263203

Classifying primary central nervous system lymphoma from glioblastoma using deep learning and radiomics based machine learning approach - a systematic review and meta-analysis

Amrita Guha,[1,*] Jayant S. Goda,[1,*] Archya Dasgupta,[2] Abhishek Mahajan,[1] Soutik Halder,[3] Jeetendra Gawde,[3] and Sanjay Talole[3]

Meta analysis of studies comparing DL/ ML with gold standard Pathology diagnosis

Clinical Radiology
The Royal College of Radiologists

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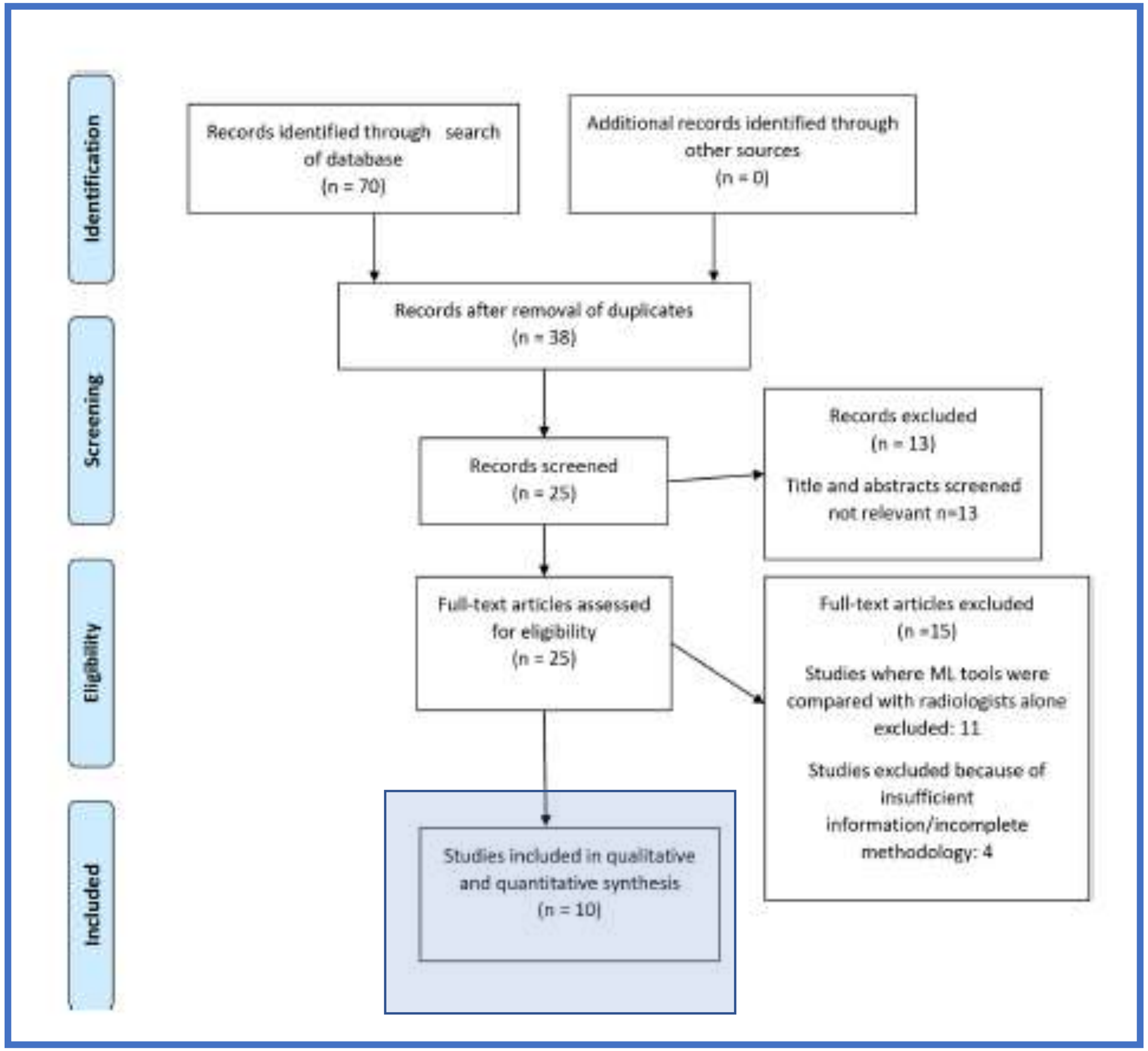
How does deep learning/ machine learning perform in comparison to radiologists in distinguishing Glioblastomas (or grade IV Astrocytomas) from Primary CNS Lymphomas?: A meta-analysis and systematic review

Amrita Guha • Soutik Halder • Shubham H. Shinde • Jitendra Gawde • Satish Munnolli • Sanjay Talole • Jayant S. Goda

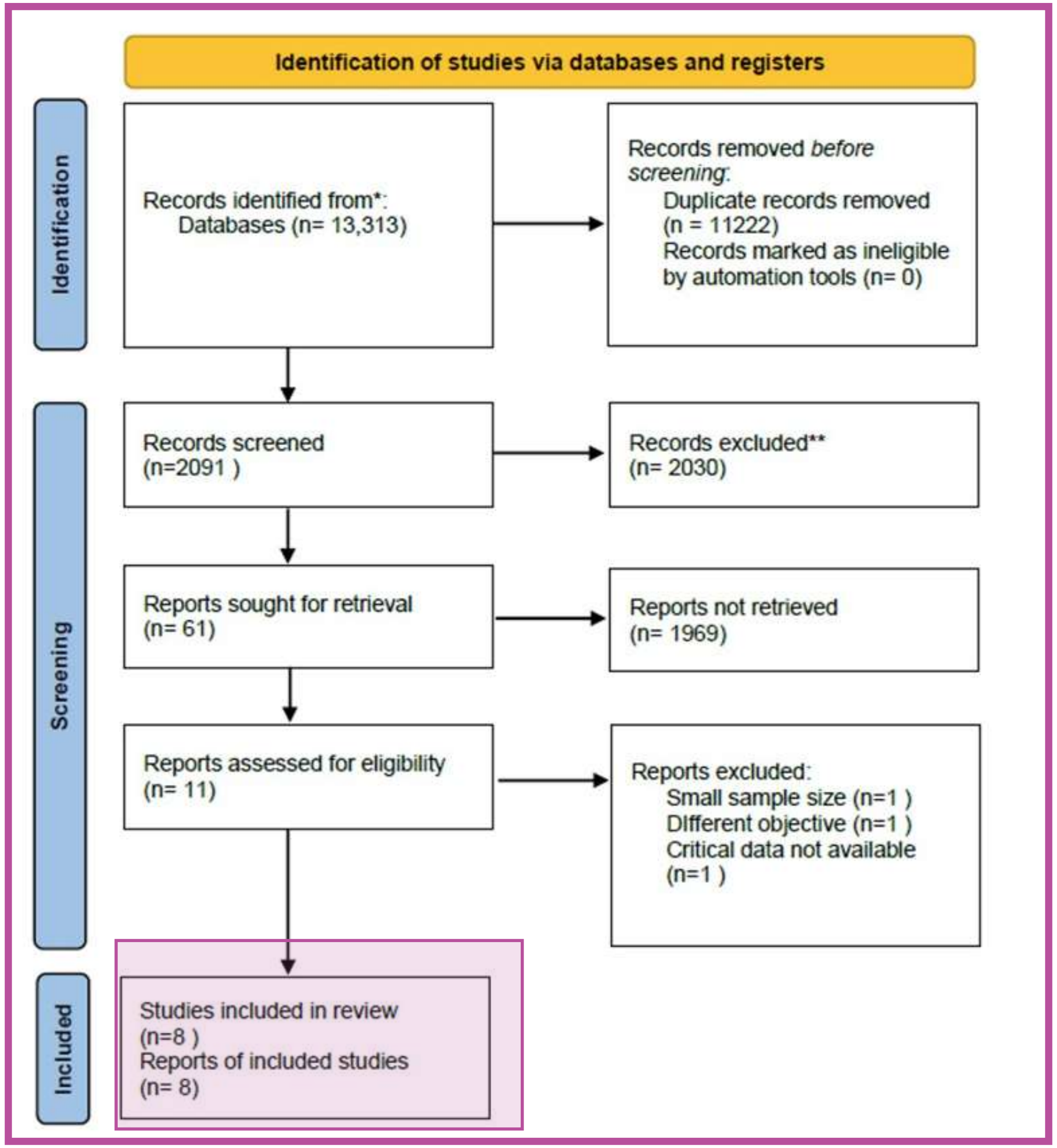
Meta analysis of studies comparing DL/ ML with radiologist in discriminating GBM from PCNSL

Classifying PCNSL from GBM by DL/ ML Approach

studies comparing DL/ ML with Pathology



studies comparing DL/ ML with Radiologist



Development and validation of radiomic signature for predicting overall survival in advanced-stage cervical cancer

Radiomic feature selection

Feature selection technique	Feature type	Number of features selected	Accuracy with selected features	Kappa value
Recursive Feature Elimination with Logistic regression	Clinical	5	0.69	0.31
	Radiomics	3	0.64	0.17
	Clinical + Radiomics	5	0.68	0.26
Recursive Feature Elimination with Random Forest	Clinical	5	0.68	0.32
	Radiomics	4	0.72	0.38
	Clinical + Radiomics	5	0.77	0.46

Feature selection function	ML algorithm	Prediction model	Accuracy	Precision	Recall	F1-Score	AUCh
Logistic regression	Logistic Regression	LR-Clinical-B	0.61	0.63	0.62	0.62	0.65
		LR-Clinical	0.61	0.63	0.62	0.6	0.65
		LR-Radiomics-B	0.76	0.83	0.76	0.78	0.60
		LR-Radiomics	0.71	0.77	0.71	0.73	0.62
		LR-Combined-B	0.71	0.77	0.71	0.73	0.56
		LR-Combined	0.76	0.78	0.76	0.77	0.51
Random forest	Random Forest	RF-Clinical-B	0.67	0.7	0.67	0.67	0.65
		RF-Clinical	0.76	0.77	0.76	0.76	0.71
		RF-Radiomics-B	0.86	0.86	0.86	0.85	0.82
		RF-Radiomics	0.81	0.81	0.81	0.81	0.81
		RF-Combined-B	0.81	0.81	0.81	0.81	0.70
		RF-Combined	0.81	0.78	0.81	0.78	0.71
	Support Vector Classifier	SV-Clinical-B	0.62	0.38	0.62	0.47	0.39
		SV-Clinical	0.62	0.38	0.62	0.47	0.59
		SV-Radiomics-B	0.76	0.76	0.76	0.76	0.70
		SV-Radiomics	0.71	0.74	0.71	0.69	0.83
		SV-Combined-B	0.76	0.83	0.76	0.78	0.82
		SV-Combined	0.81	0.85	0.81	0.82	0.82
	Gradient Boosting	GB-Clinical-B	0.67	0.66	0.67	0.66	0.68
		GB-Clinical	0.62	0.6	0.62	0.61	0.68
		GB-Radiomics-B	0.76	0.83	0.76	0.78	0.74
		GB-Radiomics	0.76	0.83	0.76	0.78	0.82
		GB-Combined-B	0.76	0.78	0.76	0.77	0.74
		GB-Combined	0.76	0.74	0.76	0.75	0.72

Step 1: 121 stable radiomic features
Step 2: top 7 clinical features and top 15 radiomic features.
Step 3:

Classifying PCNSL from GBM by DL/ ML Approach

studies comparing DL/ ML with Pathology

Author	Year	Sample Size (N)	Accuracy (%)	Sensitivity (%)	Specificity (%)	Balanced Accuracy (%)	AUC (%)
Chen Y (1)	2018	96	90.6	80.0	95.5	87.8	98.2
Xiao DD (2)	2018	82	82.0	78.0	91.0	84.5	90.0
Wu G (3)	2018	102	94.5	90.0	96.0	93.0	NA
Shrot S (5)	2019	53	93.6	100	100	100	NA
Chen C (6)	2020	138	97.9	98.2	97.6	97.9	97.8
Park JE (7)	2020	260	NA	95.0	76.0	85.5	89.0
Escoda A (8)	2020	95	93.0	93.0	92.0	92.5	NA
Bathla G (9)	2021	94	93.4	97.0	87.1	92.1	97.7
McAvoy (10) M	2021	248	94.0	87.0	100	93.5	95.0
Kim Y (4)	2018	143	94.7	96.6	92.9	94.7	95.6

- **The diagnostic metrics for AI/ML for discriminating PCNSL from GBM were high and comparable to Pathology**
- Limited by the number of studies and heterogeneity.
- Cautious regarding over fitting of models.

Classifying PCNSL from GBM by DL/ ML Approach

studies comparing DL/ ML with Radiologist

Diagnostic Metrics of Machine learning/ Deep Learning models

Sr. No.	Study	Sample Size	Accuracy	Sensitivity	Specificity	AUC
1	Yamashita K 2008	70	0.879	0.877	0.881	0.949
2	Alcaide-Leon P 2017	106	0.849	0.743	0.9	0.877
3	Nakagawa M 2018	70	0.9164	0.889	0.9438	0.98
4	Suh H B 2018	77	0.896	0.913	0.889	0.921
5	Kang D 2018	112	0.833	0.857	0.821	0.946
6	Yun J 2019	195	0.875	0.929	0.821	0.947
7	Xia W 2020	240	0.912	0.891	0.933	0.943
8	Xia W 2021	289	0.899	0.934	0.867	0.964

Diagnostic metrics of Radiologists

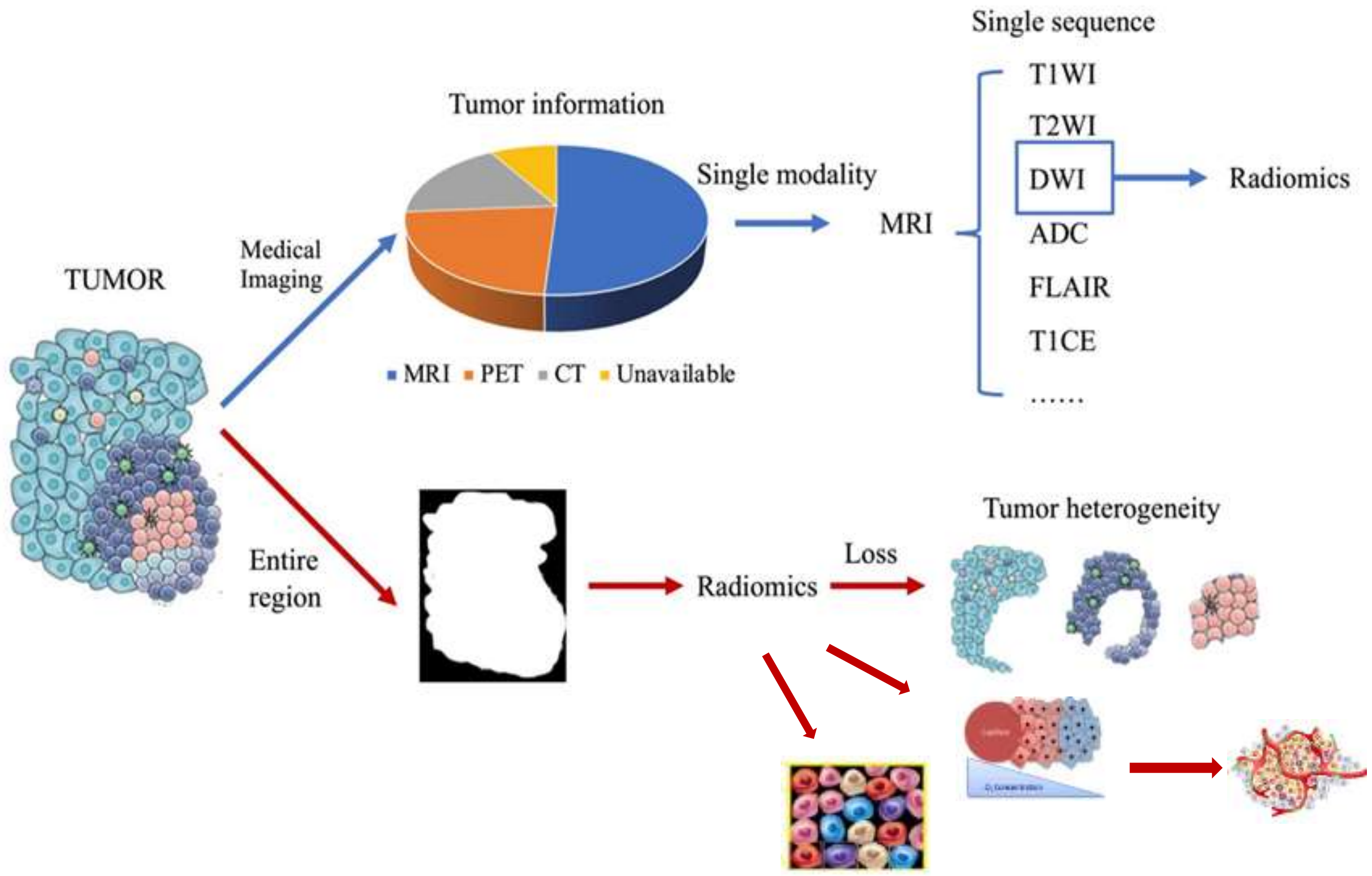
Sr. No.	Study	Sample Size	Accuracy	Sensitivity	Specificity	AUC
1	Yamashita K 2008	70	0.869	0.785	0.897	0.899
2	Alcaide-Leon P 2017	106	0.849	0.771	0.887	0.899
3	Nakagawa M 2018	70	0.729	0.703	0.755	0.84
4	Suh H B 2018	77	0.623	0.754	0.58	0.759
5	Kang D 2018	112	0.93	0.897	0.964	0.93
6	Yun J 2019	195	0.854	0.7915	0.9165	0.9225
7	Xia W 2020	240	0.945	0.913	0.978	0.945
8	Xia W 2021	289	0.906	0.853	0.954	NA

- **DL/ML tools can complement radiologists in classifying PCNSL from GBM**.
- **The role of radiologists cannot be undermined since AI is prone to over fitting**.
- DL/ML performed better than radiologist with superior sensitivity and accuracy.
- Radiologists showed better specificity, this could be attributed to their experience

Radiomic features are biologic correlates of tumor heterogeinity

	Feature categories	Example radiomic features
Morphometric	Size	Area
		Volume
		Maximum 3D diameter
		Major axis length
		Minor axis length
		Surface area
Morphometric	Shape	Elongation
		Flatness
		Sphericity
		Spherical disproportion
Intensity	First-order texture[a]	Energy
		Entropy
		10th percentile
		90th percentile
		Skewness
		Kurtosis
Intensity	Second-order texture[b]	Gray level co-occurrence matrix
		Gray level run length matrix
		Gray level size zone matrix
	High-order texture[c]	Autoregressive model
		Haar wavelet

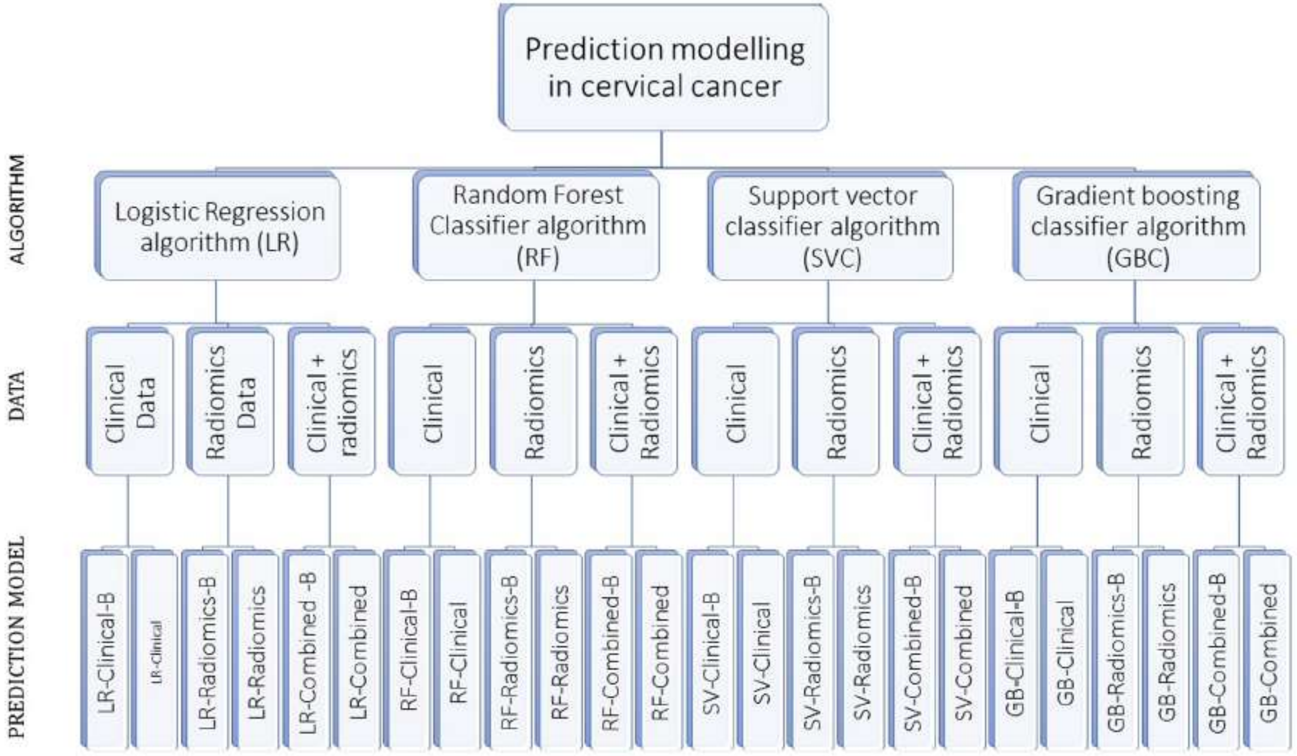
Biological Underpinning of Radiomic Signatures

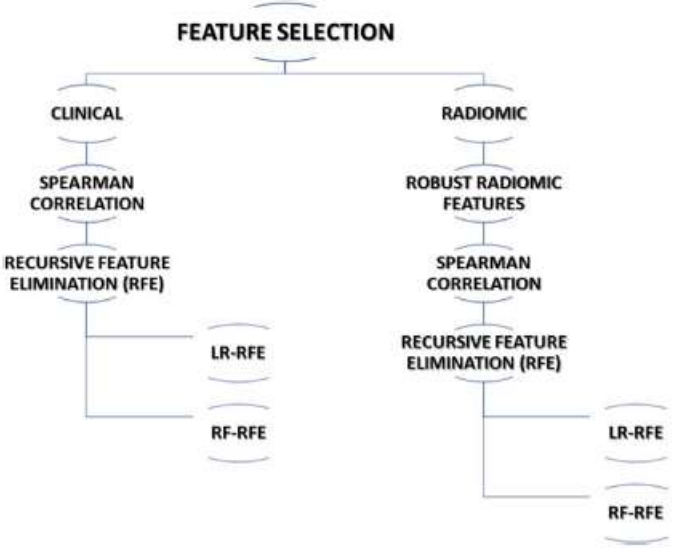


Development and validation of radiomic signature for predicting overall survival in advanced-stage cervical cancer

- Pretreatment clinical features and CT radiomic features of 68 patients, treated with CTRT

1,093 radiomic features extracted from CT images





Development and validation of radiomic signature for predicting overall survival in advanced-stage cervical cancer

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Ashish Kumar Jha[1,2,3]*, Sneha Mithun[1,2,3], Umeshkumar