A Novel Multiresolution-Statistical Texture Analysis Architecture: Radiomics-Aided Diagnosis of PDAC Based on Plain CT Images

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Presented By :

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Outline

- Introduction to the problem
- Methodology
- Results
- Implementation details and results

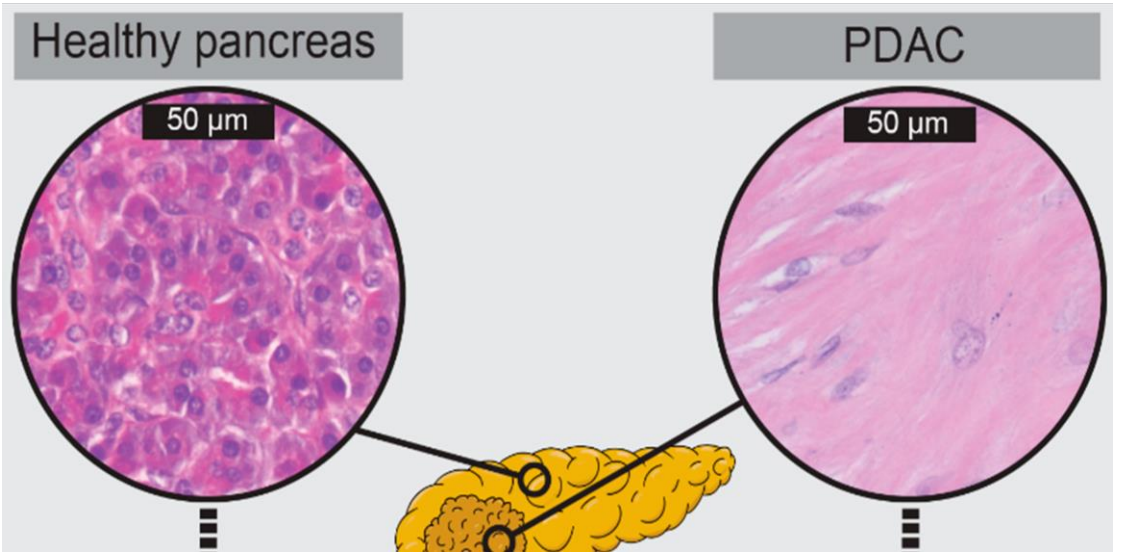
Qiu, J. J., Yin, J., Qian, W., Liu, J. H., Huang, Z. X., Yu, H. P. Ji & Zeng, X. X. (2020). A Novel Multiresolution-Statistical Texture Analysis Architecture: Radiomics-Aided Diagnosis of PDAC Based on Plain CT Images. *IEEE Transactions on Medical Imaging*, *40*(1), 12-25.

INTRODUCTION

Qiu, J. J., Yin, J., Qian, W., Liu, J. H., Huang, Z. X., Yu, H. P. Ji & Zeng, X. X. (2020). A Novel Multiresolution-Statistical Texture Analysis Architecture: Radiomics-Aided Diagnosis of PDAC Based on Plain CT Images. *IEEE Transactions on Medical Imaging*, *40*(1), 12-25.

Problem Statement

- PDAC – Pancreatic ductal adenocarcinoma – Type of malignant tumor
- CT imaging is a frequently used non-invasive examination method for PDAC
  - Plain CT
  - Contrast enhanced CT
- Limitations:
  - Subjective judgement
  - No access contrast enhancement
  - Allergic reactions or renal toxicity caused by contrast agent



Radiomics and AI

- Quantitative features of radiomics can provide interpretability.
- Radiomics + AI plays important role in early diagnosis of PDAC based on plain CT
- Radiomics Studies in previous works (pancreatic tumor related)
    - LoG (Laplacian of Gaussian) , Histogram features
    - GLCM (Gray-level co-occurrence matrix), GLRLM (Gray-level run-length matrix), ACM (Angle co-occurrence matrix)
    - Wavelet transform features

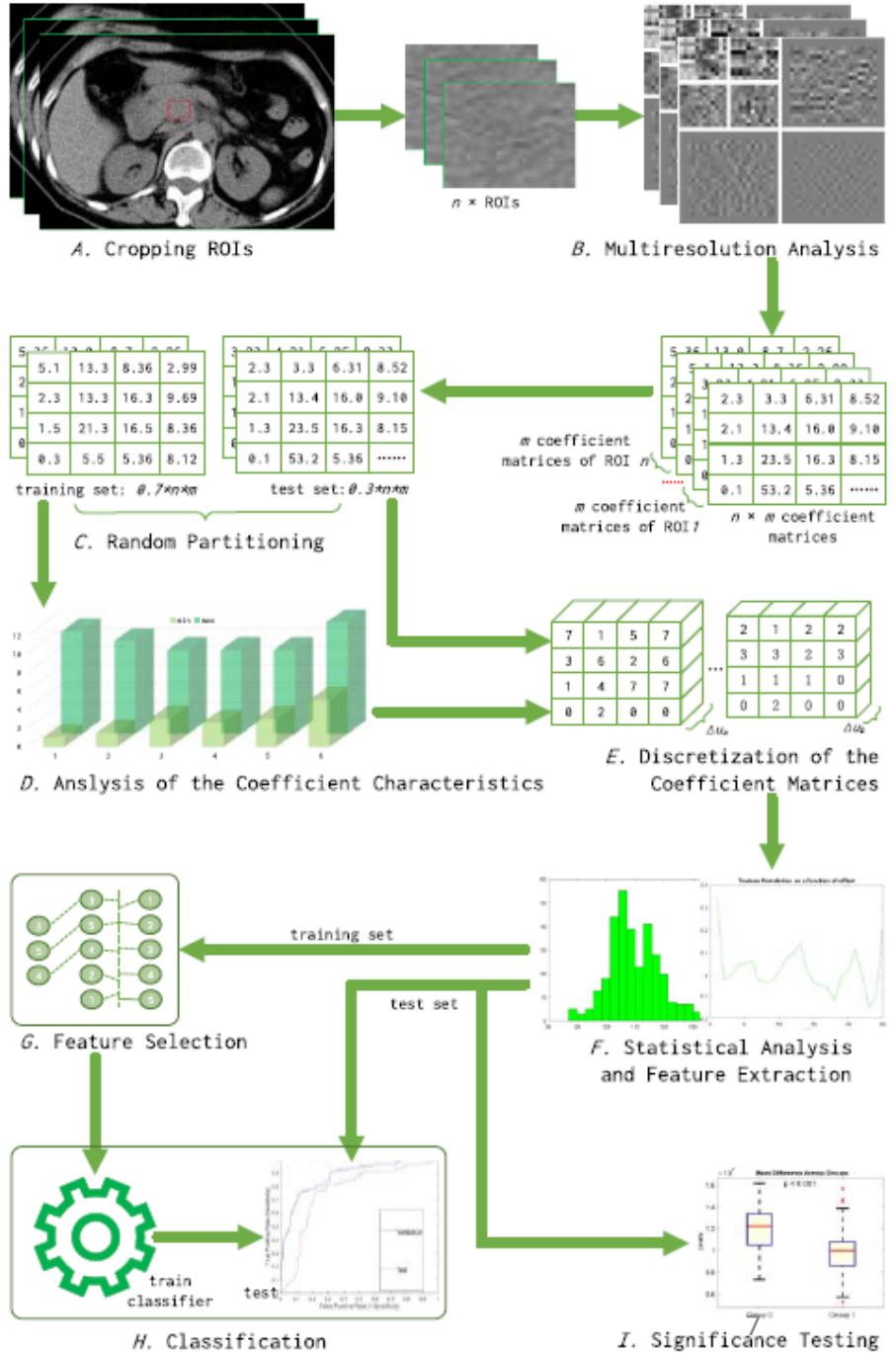
W. L. Bi, A. Hosny, M. B. Schabath, M. L. Giger, N. J. Birkbak, A. Mehrtash, T. Allison, O. Arnaout, C. Abbosh, I. F. Dunn, and R. H. Mak, "Artificial intelligence in cancer imaging: Clinical challenges and applications," *CA, Cancer J. Clinicians*, vol. 69, no. 2, pp. 127–157, 2019

METHODOLOGY

Qiu, J. J., Yin, J., Qian, W., Liu, J. H., Huang, Z. X., Yu, H. P. Ji & Zeng, X. X. (2020). A Novel Multiresolution-Statistical Texture Analysis Architecture: Radiomics-Aided Diagnosis of PDAC Based on Plain CT Images. *IEEE Transactions on Medical Imaging*, *40*(1), 12-25.

Overview

- ✓Cropping ROIs
- ✓Multiresolution Analysis :
  - ✓Wavelet transform
  - ✓Wavelet packet transform
  - ✓Contourlet transform
- ✓Random Partitioning
- ✓Analysis of Coefficient Characteristics
- ✓Discretization of the coefficient matrices
- ✓Statistical Analysis and Feature extraction
- ✓Feature selection
- ✓Classification and Significance testing



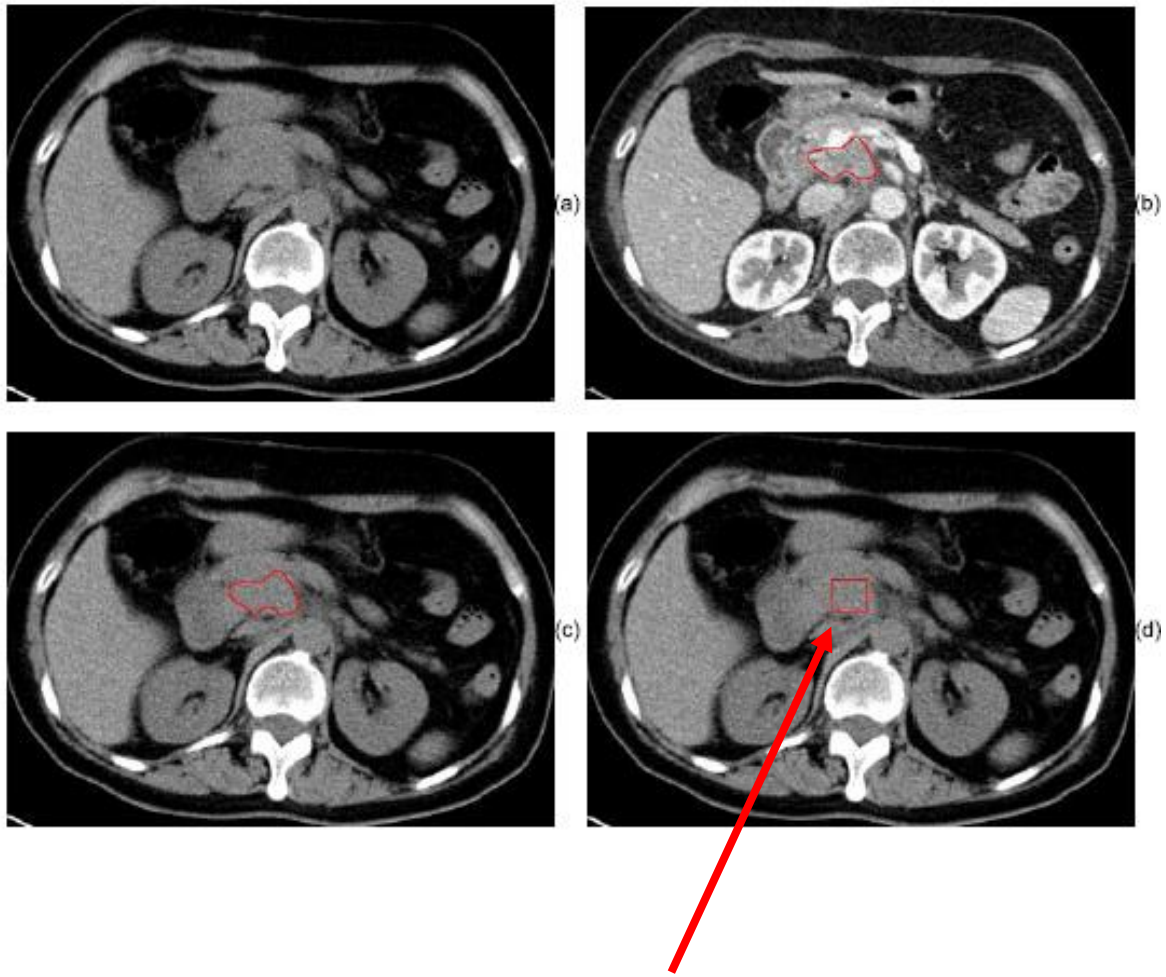
Dataset

- Subjects
  - 153 PDAC
    - 92 male; 61 female
    - Age : 30-84 (59.1y)
  - 159 HP
    - 104 male; 55 female
    - Age : 40 – 57 (45.9y)
- Random partition
  - Train set : Test set = 7:3

- Data acquisition setup
  - Plain CT slices (2 or 5mm thickness)
  - Window level : 40-50 HU
  - Window width : 300-350 HU
  - Enhanced CT slices may used as reference
  - Scanner : Siemens SOMATOM Definition AS+/Flash or Philips Brilliance 64 CT scanners.

Cropping ROIs

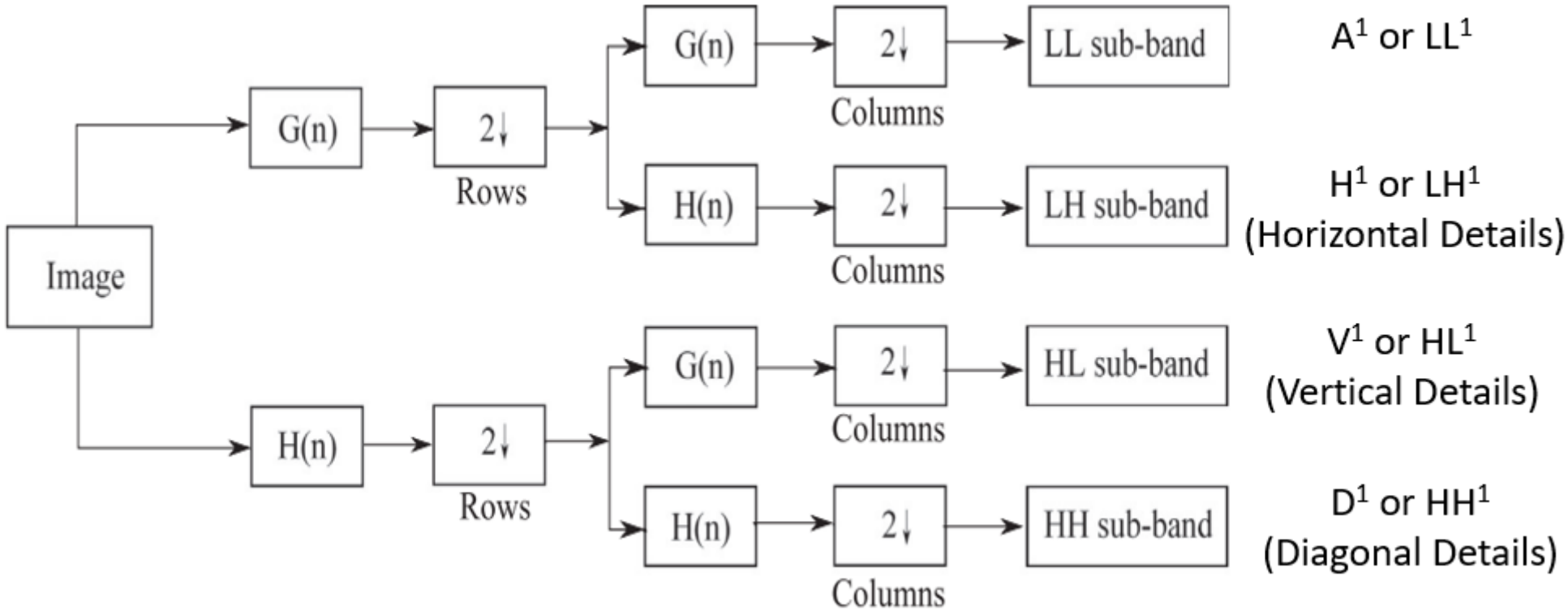
- Cropping strategy
  - PDAC – Slice with largest cross-sectional area of tumor
  - HP – Slice with largest cross-sectional area of HP.
- ROI acquisition
  - By 3 senior radiologists (>6y experience)



Multiresolution Analysis

Wavelet transform, Wavelet packet transform and Contourlet transforms

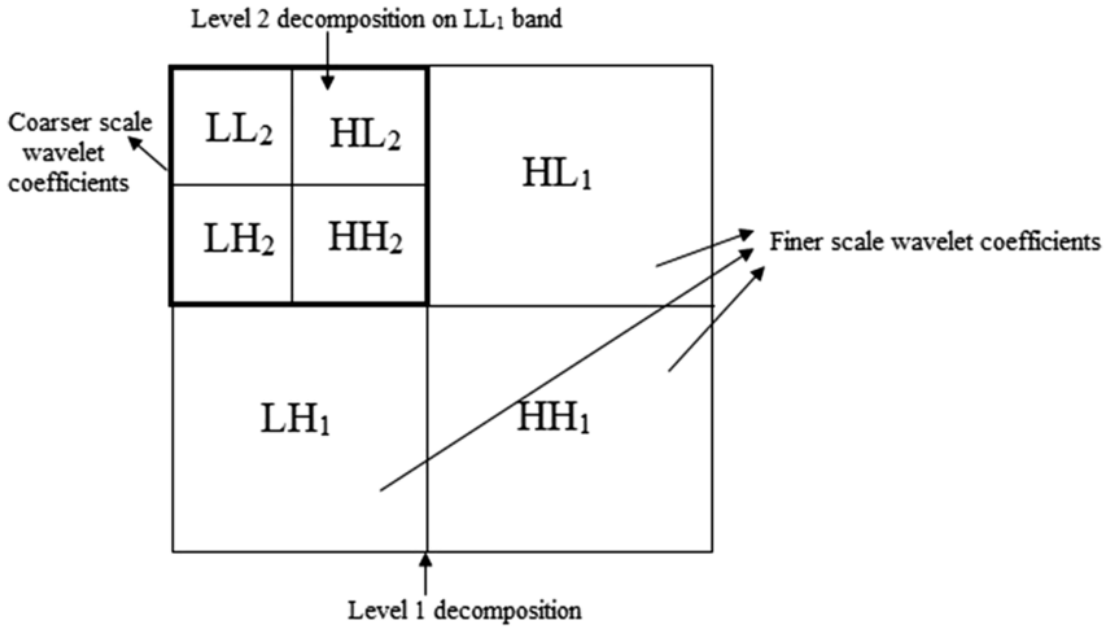
- Decompose an ROI into multiple sub-band components.

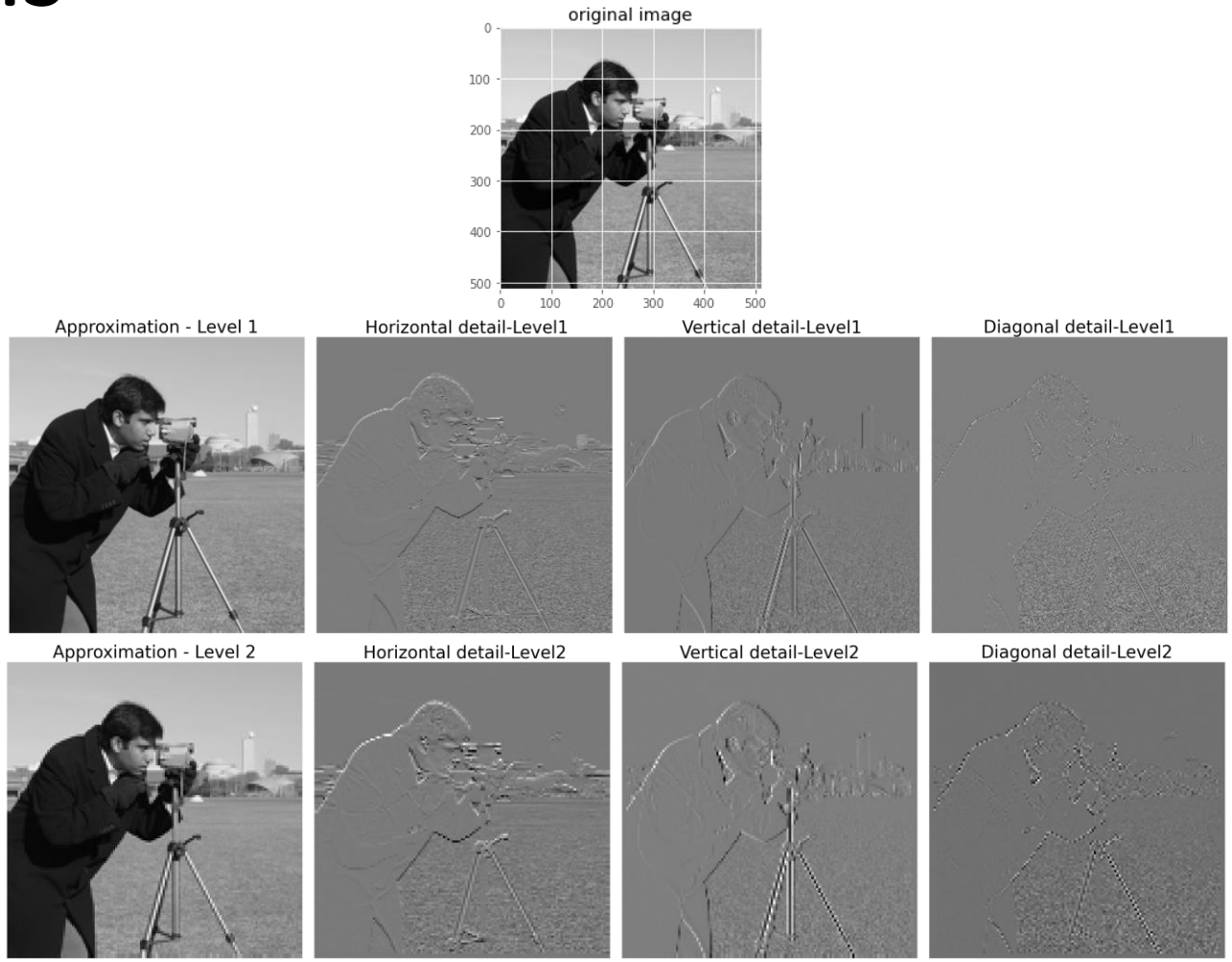


https://www.mathworks.com/help/wavelet/ref/dwt2.html

Multiresolution Analysis

- Wavelet Name : bior1.3
- 2 level decomposition





Analysis of Coefficient Characteristics (Based on trainset)

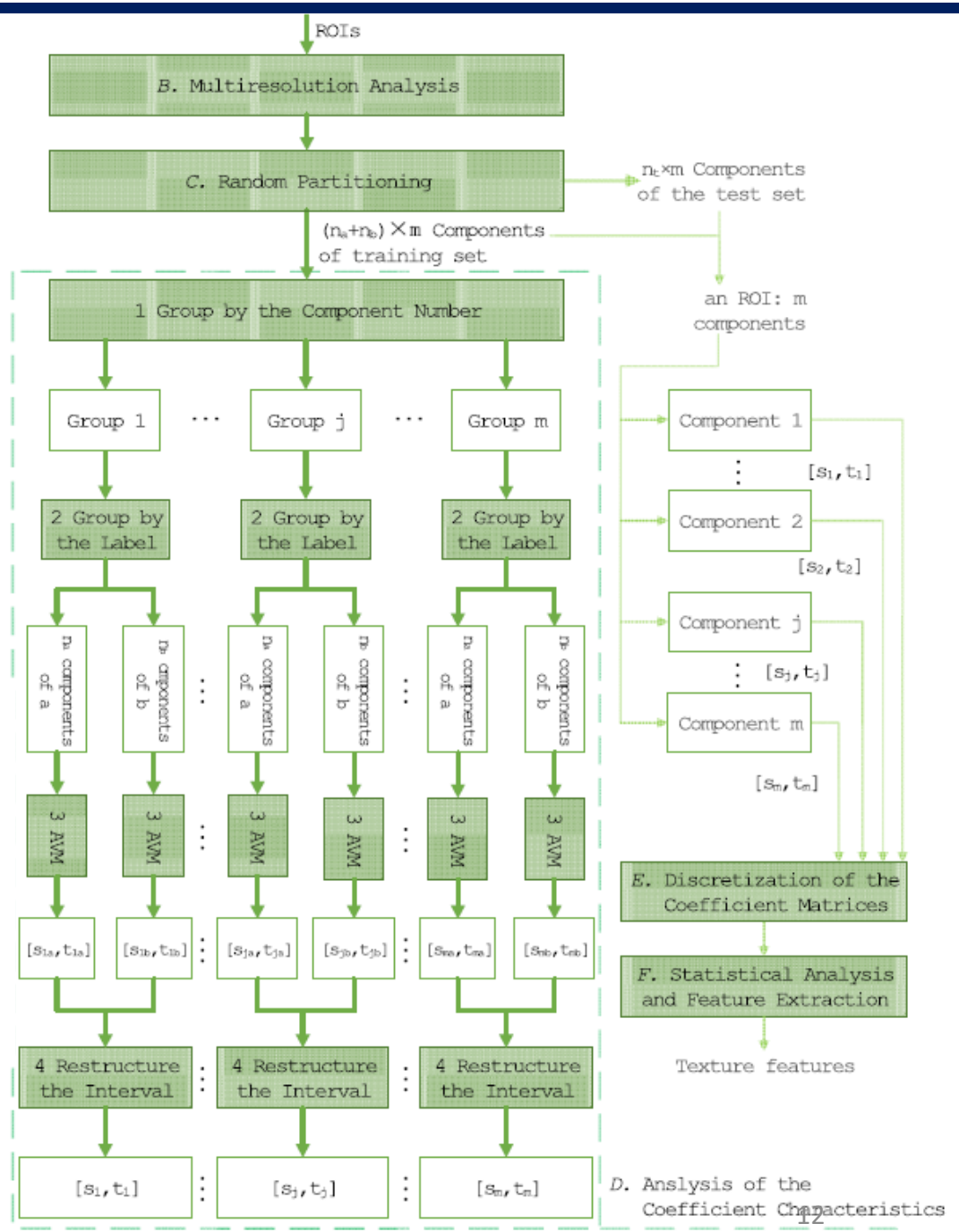
- Group by component number
- Group by label
- Find averages of min and max
- Structure the interval

$$x_{ji} = \min\left(C_{ji} = \begin{bmatrix} c_{11} & \cdots & c_{1l} \\ c_{21} & \ddots & \vdots \\ \cdots & \cdots & c_{kl} \end{bmatrix}\right) \qquad s_{ja} = \frac{\sum_{i=1}^{n_a} x_{ji}}{n_a}, \quad s_{jb} = \frac{\sum_{i=1}^{n_b} x_{ji}}{n_b}$$

$$y_{ji} = \max\left(C_{ji} = \begin{bmatrix} c_{11} & \cdots & c_{1l} \\ c_{21} & \ddots & \vdots \\ \cdots & \cdots & c_{kl} \end{bmatrix}\right) \qquad t_{ja} = \frac{\sum_{i=1}^{n_a} y_{ji}}{n_a}, \quad t_{jb} = \frac{\sum_{i=1}^{n_b} y_{ji}}{n_b}$$

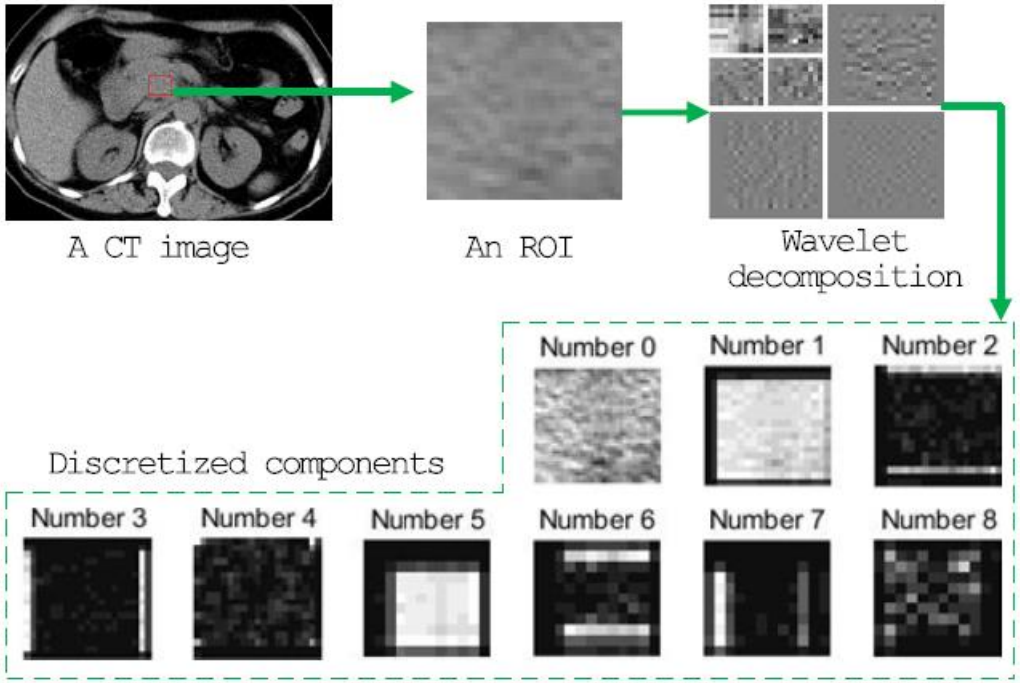
$$s_j = \min\left(s_{ja}, s_{jb}\right)$$

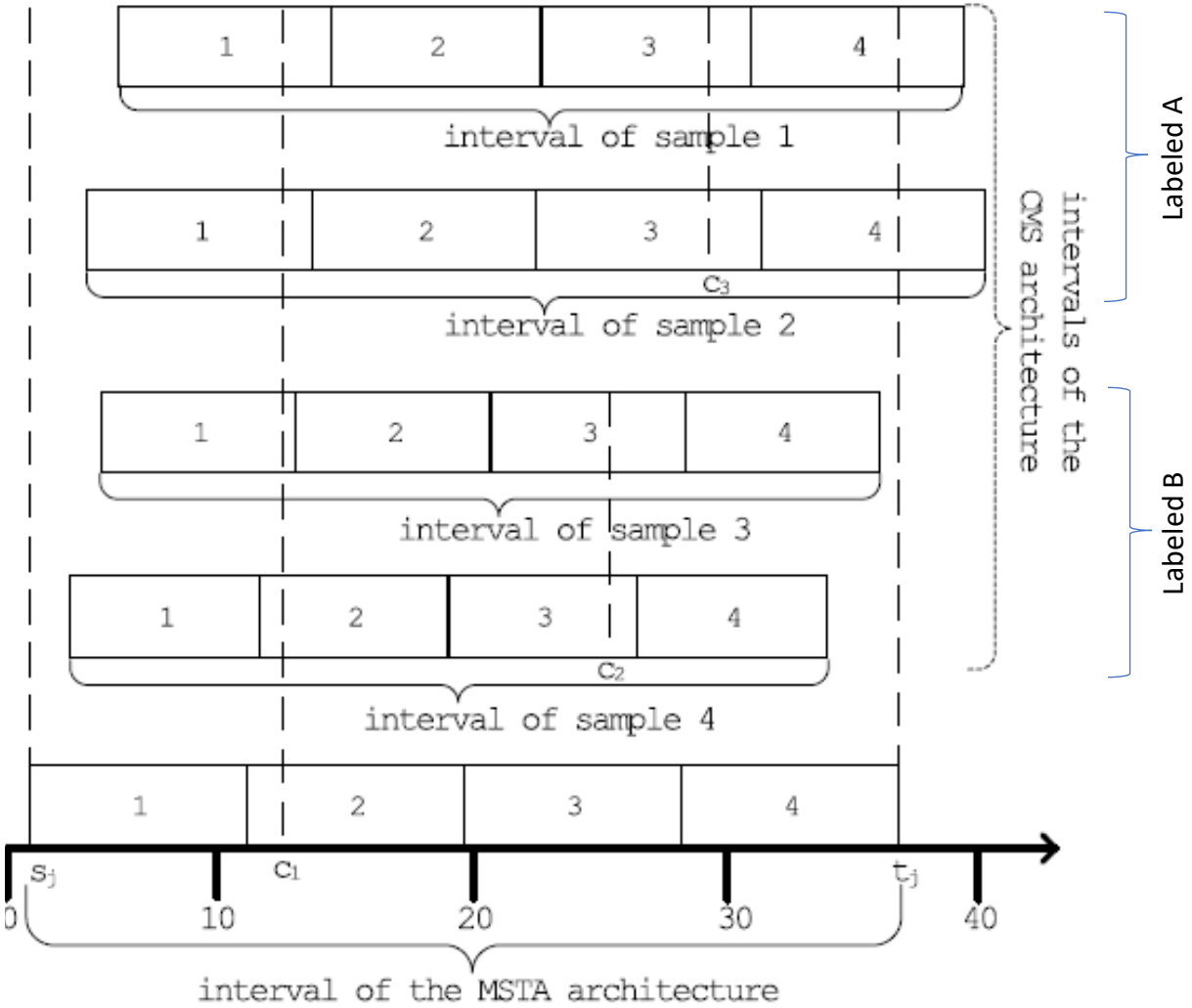
$$t_j = \max\left(t_{ja}, t_{jb}\right)$$



Discretization of the coefficient matrices

- Number of bins = 8/16/24





Statistical Analysis and Feature extraction

Coefficient statistics (3)	Histograms (7)	Gray-level cooccurrence matrix (5)	Gray level run-length matrix (11)
Mean	Mean	Contrast	Short-run emphasis
Variance	Standard deviation	Correlation	Long-run emphasis
Average Energy	Smoothness	Energy	Gray-level non-uniformity
	Cubic moment	Homogeneity	Run-length non-uniformity
	Uniformity	Entropy	Run percentage
	Entropy		Low gray-level run emphasis
	Fourth moment		High gray-level run emphasis
			Short run low gray-level emphasis
			Short run high gray-level emphasis
			Long run low gray-level emphasis
			Long run high gray-level emphasis

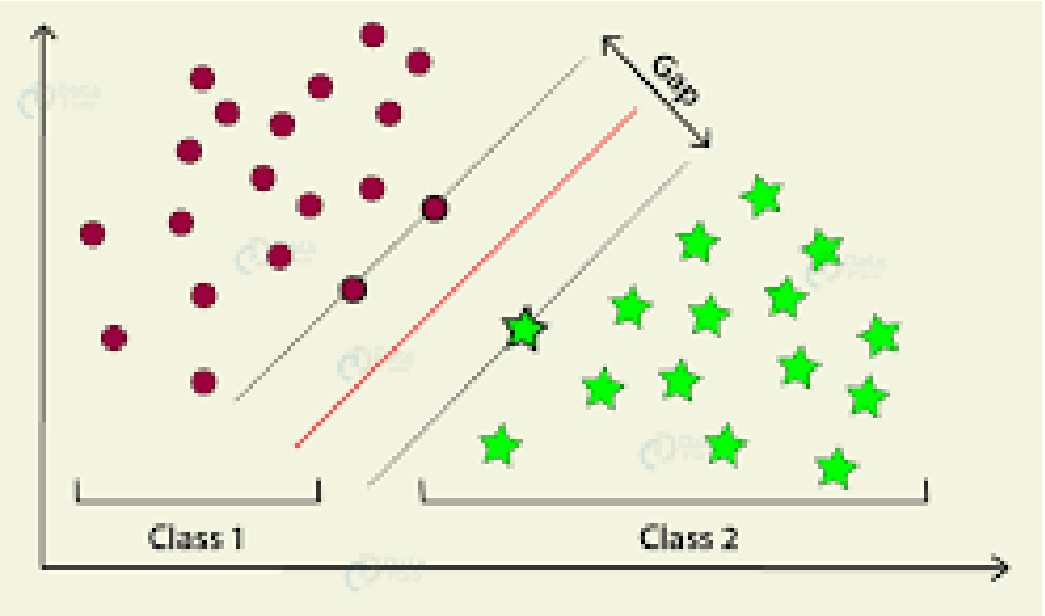
Feature selection

- ILFS (Infinite Latent Feature Selection) algorithm proposed by G.Roffo et al.
- Ranking of all the features based on trainset and selected the first k features.
  - K < 20 (empirically limited)

https://www.mathworks.com/matlabcentral/fileexchange/56937-feature-selection-library,

Classification and Significance testing

- Experimented with multiple ML methods and selected SVM (with linear kernel).
  - Outstanding performance with small sample size
  - Widely used in radiomics studies
  - Interpretability
  - Generalization
- 10-fold cross validation
- Mann-Whitney U tests
  - Non-parametric test



RESULTS

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Classification - Results

- On test set

TABLE IV

TEST RESULTS OF THE CLASSIFICATIONS: ACC (%), ACCURACY; SEN (%), SENSITIVITY; SPE (%), SPECIFICITY. THE BOLD AND ITALIC TEXTS HIGHLIGHT THE HIGHEST PERFORMANCES OBTAINED FOR AN INDICATOR

No.	Method	ACC	SEN	SPE	AUC	No.	Method	ACC	SEN	SPE	AUC
1	GLS	74.47	73.91	75	0.726	6	ACM	62.77	56.52	68.75	0.671
2	GLH	70.21	63.04	77.08	0.772	7	LOG	70.21	67.39	72.92	0.693
3	GLCM	61.7	47.83	75	0.729	8	WT	71.28	69.57	72.92	0.715
4	GLRLM	72.34	69.57	75	0.767	9	WPT	72.34	71.74	72.92	0.701
5	GL-M	73.4	65.22	***81.25***	0.744	10	CT	69.15	67.39	70.83	0.727
11	CMS-W-CS	71.28	69.57	72.92	0.747	16	MSTA-W-CS	74.47	71.74	77.08	0.743
12	CMS-W-H	73.4	71.74	75	0.749	17	MSTA-W-H	73.4	69.57	77.08	0.746
13	CMS-W-COM	63.83	54.35	72.92	0.726	18	MSTA-W-COM	71.28	65.22	77.08	0.753
14	CMS-W-RLM	72.34	69.57	75	0.743	19	MSTA-W-RLM	***77.66***	78.26	77.08	0.778
15	CMS-W-M	73.4	71.74	75	0.752	**20**	**MSTA-W-M**	***77.66***	**78.26**	**77.08**	***0.792***
21	CMS-WP-CS	73.4	71.74	75	0.738	26	MSTA-WP-CS	72.34	73.91	70.83	0.73
22	CMS-WP-H	73.4	76.09	70.83	0.744	27	MSTA-WP-H	74.47	76.09	72.92	0.747
23	CMS-WP-COM	51.06	0	100	0.5	28	MSTA-WP-COM	68.09	56.52	79.17	0.757
24	CMS-WP-RLM	72.34	69.57	75	0.753	**29**	**MSTA-WP-RLM**	***77.66***	**78.26**	**77.08**	**0.787**
25	CMS-WP-M	75.53	73.91	77.08	0.791	30	MSTA-WP-M	75.53	***80.43***	70.83	0.765
31	CMS-C-CS	61.7	47.83	75	0.647	36	MSTA-C-CS	71.28	71.74	70.83	0.768
32	CMS-C-H	71.28	73.91	68.75	0.781	37	MSTA-C-H	71.28	67.39	75	0.769
33	CMS-C-COM	63.83	54.35	72.92	0.703	38	MSTA-C-COM	65.96	52.17	79.17	0.742
34	CMS-C-RLM	72.34	69.57	75	0.752	**39**	**MSTA-C-RLM**	***77.66***	**78.26**	**77.08**	**0.777**
35	CMS-C-M	69.15	65.22	72.92	0.771	**40**	**MSTA-C-M**	**75.53**	**71.74**	**79.17**	**0.781**

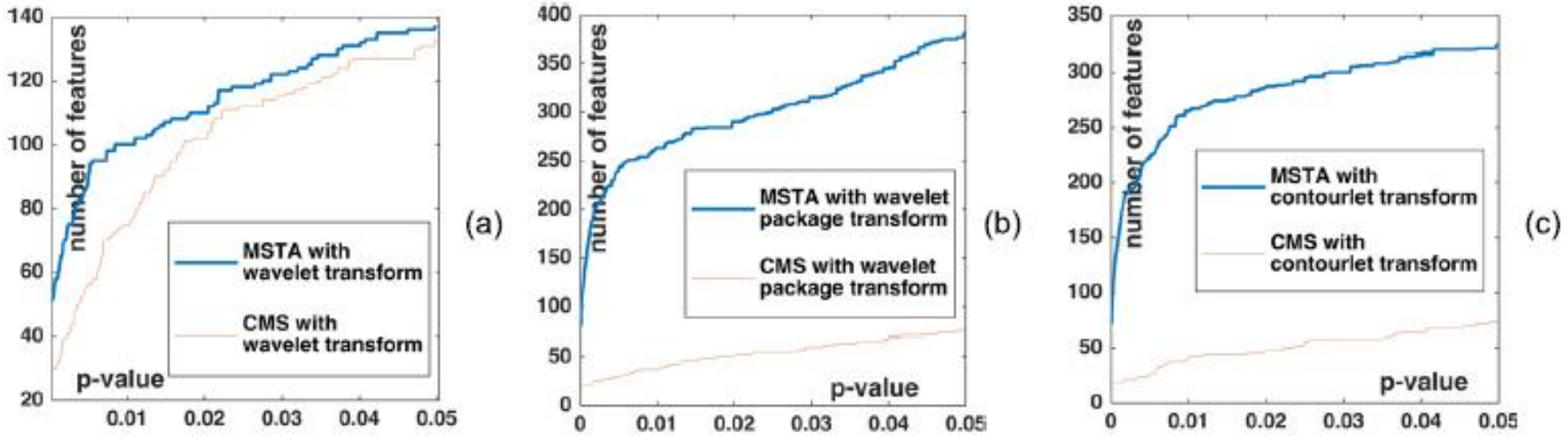
Classification - Results

TEXTURE ANALYSIS	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	1.10	1.11	1.12	1.13	1.14	1.15	1.16
	1.17	1.18	1.19	1.20	1.21	1.22	1.23	1.24	1.25							
MSTA-W-CS	64.7	64.7	70.2	72.9	68.3	72.0	73.4	71.6	**72.9**	69.7	64.2	61.0	73.4	72.0	67.0	66.1
	71.6	70.2	64.7	64.7	**73.9**	70.2	72.0	65.1	67.9							
MSTA-W-H	70.6	70.6	72.5	70.2	67.4	70.6	**75.7**	72.5	**75.2**	70.6	65.1	55.0	73.4	74.3	62.4	70.2
	75.2	70.2	67.9	69.7	72.9	72.5	74.3	72.0	71.6							
MSTA-W-COM	74.8	74.8	73.4	70.6	Failed	73.4	69.3	69.3	**73.4**	**78.0**	72.9	70.6	75.2	72.9	69.3	70.6
	70.2	72.9	71.1	72.0	76.1	73.9	71.1	67.4	75.2							
MSTA-W-RLM	69.3	70.2	75.7	75.7	70.2	71.6	75.7	73.4	**75.7**	72.0	63.3	72.5	75.2	75.2	70.6	72.0
	71.6	74.3	72.9	73.9	73.9	74.3	**78.4**	74.3	72.5							
MSTA-W-M	75.2	75.2	71.1	75.7	Failed	76.6	77.5	76.6	**79.8**	76.1	68.3	74.3	76.6	76.1	67.4	75.2
	75.2	74.8	75.7	76.1	74.3	78.9	75.7	67.4	74.3							

1.1 fine tree; 1.2 medium tree; 1.3 coarse tree; 1.4 linear discriminant; 1.5 quadratic discriminant; 1.6 logistic regression; 1.7 Gaussian naïve Bayes; 1.8 kernel naïve Bayes; **1.9 linear SVM**; 1.10 quadratic SVM; 1.11 cubic SVM; 1.12 fine Gaussian SVM; 1.13 medium Gaussian SVM; 1.14 coarse Gaussian SVM; 1.15 fine KNN; 1.16 medium KNN; 1.17 coarse KNN; 1.18 cosine KNN; 1.19 cubic KNN: 1.20 weighted KNN; 1.21 ensemble boosted trees; 1.22 ensemble bagged trees; 1.23 ensemble subspace discriminant; 1.24 ensemble subspace KNN; 1.25 ensemble RUSBoosted tree.

Significance Tests - Results

- Statistical tests were performed based on test set.
- Number of features with statistically significant difference (MSTA vs CMS)



Significance Tests - Results

- *x :* median for PDAC; *y :* median for HP.
- The alternative hypothesis of a left-tailed test states that $x < y$
- The alternative hypothesis of a right-tailed test states that $x > y$.

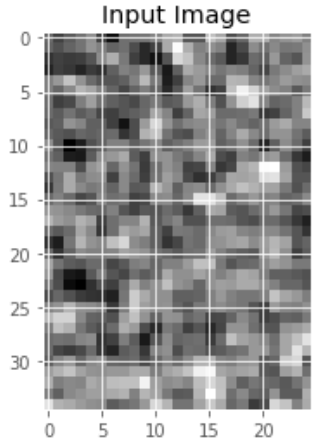
LEFT-TAILED AND RIGHT-TAILED TESTS: DIFFERENCE IN THE TEXTURE FEATURE VALUES FOR PDACS AND HPS; A, H, V, AND D ARE APPROXIMATE, HORIZONTAL, VERTICAL, AND DIAGONAL DIRECTIONS, RESPECTIVELY

No.	Texture analysis method	Component	Feature name	Two-sided p ≤	Left-tailed p ≤	Right-tailed p ≤
f1	MSTA-W-CS	D in 2-level	variance	6.66×10^{-6}	3.33×10^{-6}	
f2	MSTA-W-CS	D in 2-level	average energy	7.16×10^{-6}	3.58×10^{-6}	
f3	MSTA-W-H	A in 1-level	entropy	0.25×10^{-6}	**1.27×10^{-7}**	
f4	MSTA-W-H	A in 1-level	uniformity	1.78×10^{-6}		**8.92×10^{-7}**
f5	MSTA-W-COM	A in 1-level	d=1, homogeneity	1.09×10^{-6}	**5.45×10^{-7}**	
f6	MSTA-W-COM	A in 1-level	d=1, energy	1.78×10^{-6}		**8.99×10^{-7}**
f7	MSTA-W-RLM	D in 2-level	long-run high level emphasis	2.32×10^{-6}	1.16×10^{-6}	
f8	MSTA-W-RLM	D in 2-level	short-run emphasis	1.39×10^{-6}		6.95×10^{-6}

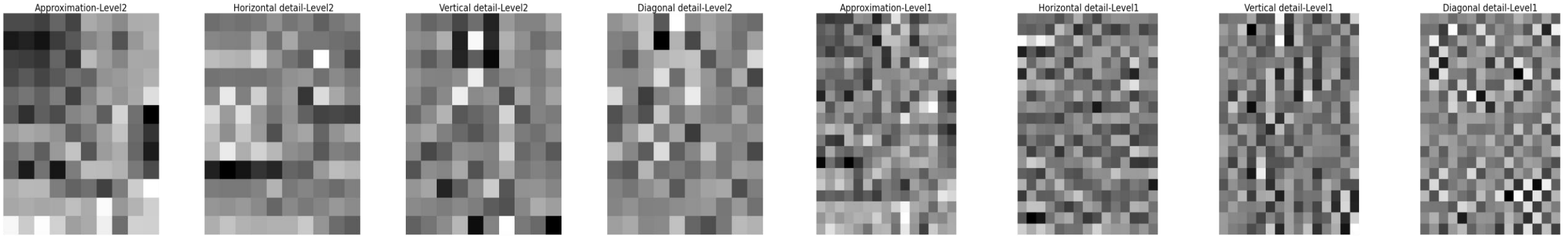
IMPLEMENTATION

https://github.com/Mithunjha/PDAC_Prediction

1. Extraction of ROI



2. Multi resolution analysis : Wavelet Transform



3. Random partitioning

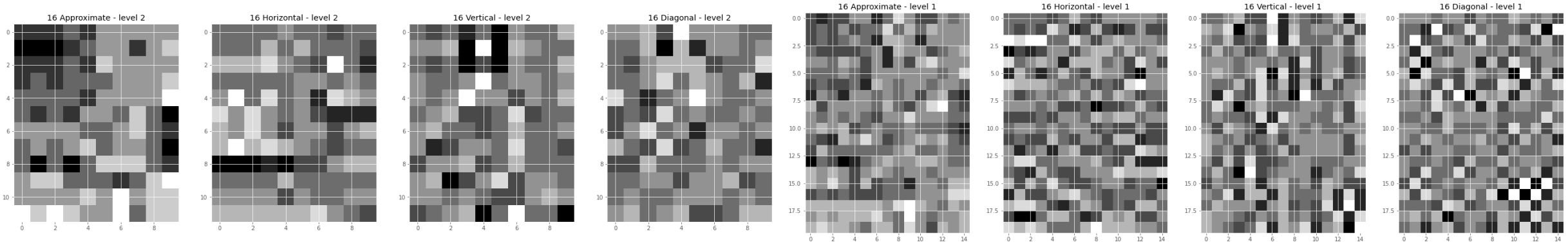
Train set : Test set = 7 : 3

Train data
Class 1 (PDAC) = 107
Class 2 (HP) = 111

Test data
Class 1 (PDAC) = 46
Class 2 (HP) = 48

https://pywavelets.readthedocs.io/en/latest/

4. Discretization (Number of bins = 8)



5. Feature Extraction

	mean_A2	std_A2	energy_A2	h_mean_A2	h_variance_A2	h_skewness_A2	h_kurtosis_A2	h_entropy_A2
0	1.464286	0.822980	2.821429	1.470028	0.679985	-0.674185	2.356045	1.076812
1	3.805556	1.308507	16.194444	3.820479	1.719129	-0.823211	3.257713	1.591262
2	3.852273	1.702537	17.738636	3.867380	2.910227	-1.092021	3.590984	1.636254

312 x 208

3 coefficient statistics features, 5 histogram features, 4 gray level co-occurrence matrices features and 11 run length matrices features

6. Feature selection – based on trainset (218)

	ShortLowGrayLevelEmphasis_A2	LowGrayLevelRunEmphasis_A2	LowGrayLevelRunEmphasis_A1	ShortLowGrayLevelEmphasis_A1
0	3.133088e+14	3.133088e+14	2.049790e+14	2.049790e+14
1	4.367321e+14	4.367321e+14	4.990584e+14	4.990584e+14
2	2.121932e+15	2.121932e+15	2.612274e+15	2.612274e+15
3	8.220777e+14	8.220777e+14	1.021465e+15	1.021465e+15
4	1.055106e-01	1.189265e-01	1.181645e-01	9.655603e-02

218 x # features

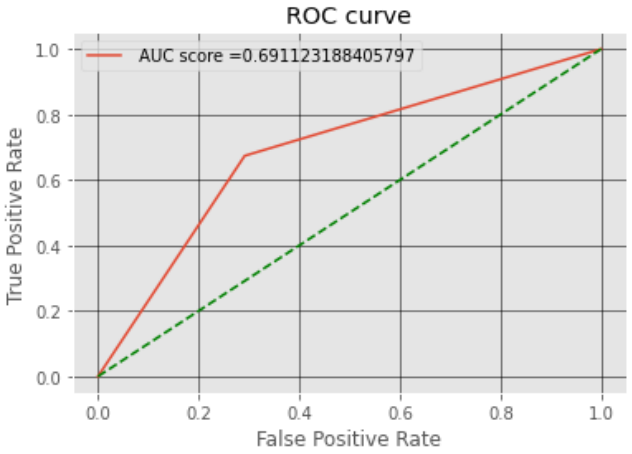
7. Classification and significance testing

Experimented with : Linear SVM, Decision tree, KNN, Poly SVM.
Significance test : Mann U Whitney test
Results are reported in following slides.

https://github.com/giakou4/pyfeats/blob/main/Features.pdf

Results

No.	Method	ACC	SEN	SPE	AUC
16	MSTA-W-CS	74.47	71.74	77.08	0.743
17	MSTA-W-H	73.4	69.57	77.08	0.746
18	MSTA-W-COM	71.28	65.22	77.08	0.753
19	MSTA-W-RLM	*77.66*	78.26	77.08	0.778
20	**MSTA-W-M**	*77.66*	**78.26**	**77.08**	*0.792*



ROC curve of SVM - Linear

- Multi resolution analysis method : wavelet transform
- Selected number of features = 20 ; Number of bins = 8
- Model = SVM

Features	Accuracy	Sensitivity	Specificity	AUC	Precision	F1
CS	72.34	73.91	70.83	0.7237	70.83	0.7234
H	64.89	60.87	68.75	0.6481	65.12	0.6292
COM	68.09	67.39	68.75	0.6807	67.39	0.6739
RLM	70.21	65.22	75.0	0.7011	71.43	0.6818
ALL	69.15	67.39	70.83	0.6911	68.88	0.6813

Results

- Selected number of features = 20
- Feature extraction = ALL

```
Train Accuracy:  0.7752293577981652
Test Accuracy:  0.6914893617021277
Precision:  0.6888888888888889
Sensitivity:  0.6739130434782609
Specificity: 0.7083333333333334
f1:  0.6813186813186812
Area Under Curve (AUC):  0.691123188405797
Classification Report :
              precision    recall  f1-score   support

           0       0.69      0.71      0.70        48
           1       0.69      0.67      0.68        46

    accuracy                           0.69        94
   macro avg       0.69      0.69      0.69        94
weighted avg       0.69      0.69      0.69        94
```

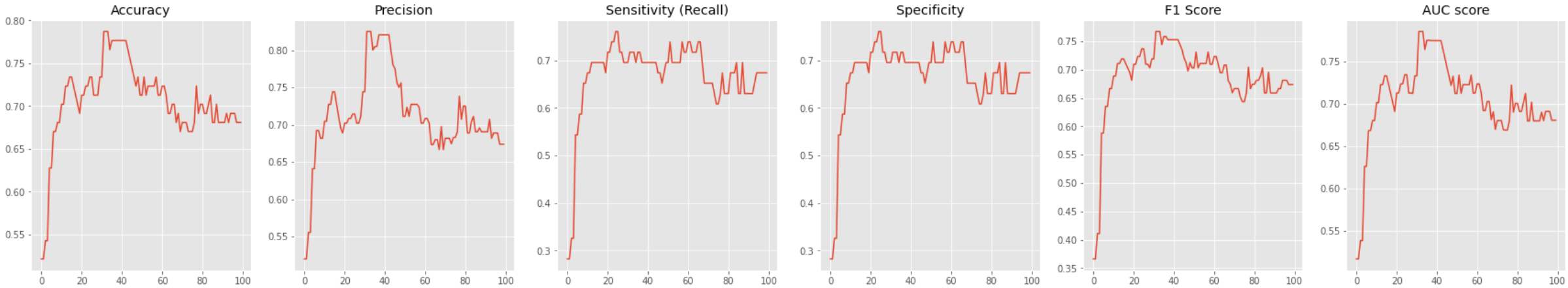
Results of Linear SVM

```
Train Accuracy:  0.8302752293577982
Test Accuracy:  0.7021276595744681
Precision:  0.7142857142857143
Sensitivity:  0.6521739130434783
Specificity: 0.75
f1:  0.6818181818181819
Area Under Curve (AUC):  0.7010869565217391
Classification Report :
              precision    recall  f1-score   support

           0       0.69      0.75      0.72        48
           1       0.71      0.65      0.68        46

    accuracy                           0.70        94
   macro avg       0.70      0.70      0.70        94
weighted avg       0.70      0.70      0.70        94
```

Results of Poly SVM

Models	Accuracy	Sensitivity	Specificity	AUC	Precision	F1
Linear SVM	69.15	67.39	70.83	0.6911	68.88	0.6813
Decision Tree	62.77	63.04	62.5	0.6277	61.70	0.6237
KNN	58.51	56.52	60.42	0.5847	57.77	0.5714
Poly SVM	70.21	65.22	75	0.7011	71.43	0.6818

- Variance of performance metrics along with number of features



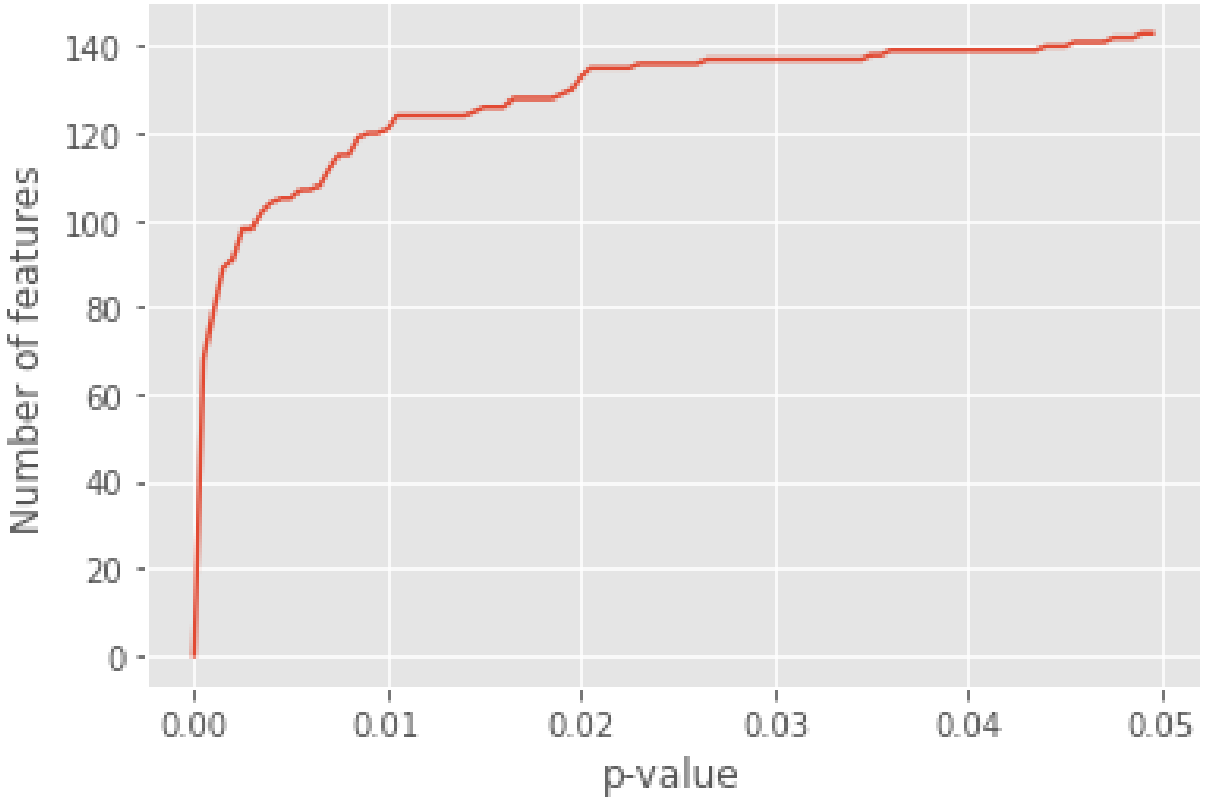
- Selected number of features = 32; Feature extraction = ALL

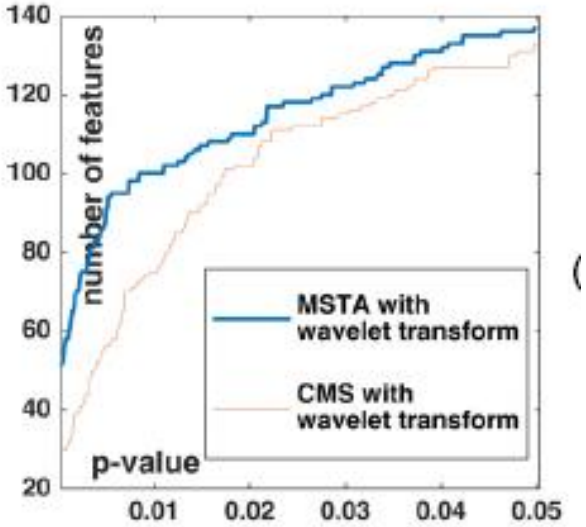
Models	Accuracy	Sensitivity	Specificity	AUC	Precision	F1
Linear SVM	78.72	71.74	71.74	0.7858	82.5	0.7674

No.	Method	ACC	SEN	SPE	AUC
16	MSTA-W-CS	74.47	71.74	77.08	0.743
17	MSTA-W-H	73.4	69.57	77.08	0.746
18	MSTA-W-COM	71.28	65.22	77.08	0.753
19	MSTA-W-RLM	***77.66***	78.26	77.08	0.778
20	**MSTA-W-M**	***77.66***	**78.26**	**77.08**	***0.792***

Statistical Testing

- Number of significant features (for different p-value)



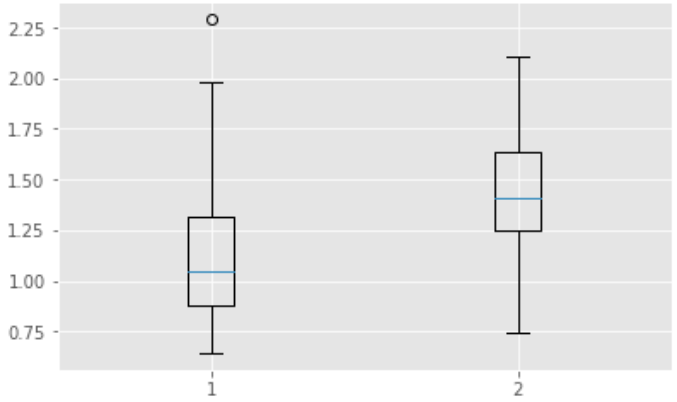


LEFT-TAILED AND RIGHT-TAILED TESTS: DIFFERENCE IN THE TEXTURE FEATURE VALUES FOR PDACs AND HPs;

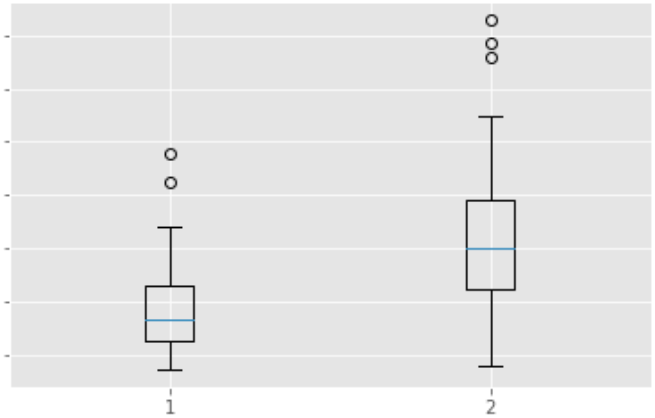
Feature name	Statistical	Component	Two sided	Less PDAC<HP	Greater PDAC>HP
Std_V2	CS - STD	Vertical – level 2	7.95e-06	3.97e-06	-
Mean_V1	CS – Mean	Vertical – level 1	2.92e-05	-	-
H_entropy_V2	H - Entropy	Vertical – level 2	7.68e-06	3.84e-06	-
H_variance_V2	H - variance	Vertical – level 2	7.96e-06	3.98e-06	-
Contrast_d2_A1	Contrast – Distance 2	Approximate – level 1	1.18e-06	5.88e-07	-
Contrast_d1_A1	Contrast – Distance 1	Approximate – level 1	1.27e-06	6.35e-07	-
LongRunEmphasis_A1	RLM – Long Run Emphasis	Approximate – level 1	1.27e-07	-	6.35e-08
ShortRunEmphasis_A1	RLM – Short Run Emphasis	Approximate – level 1	3.23e-07	1.62e-07	-

https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.mannwhitneyu.html

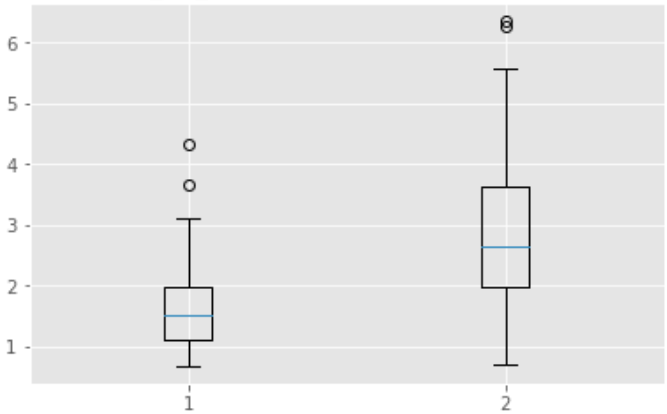
std_V2, p-value: 3.9787e-06, AUC : 0.33



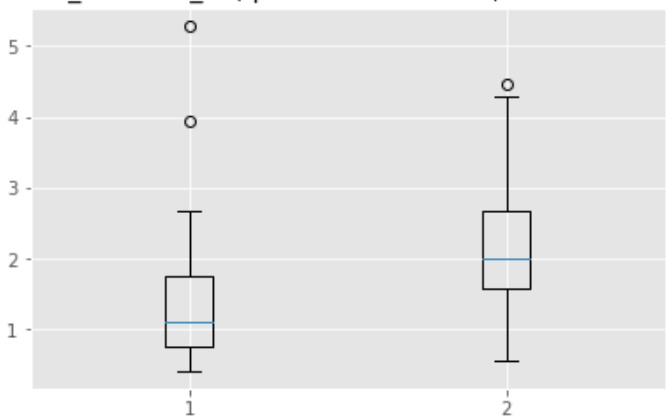
contrast_d2_A1, p-value: 5.881e-07, AUC : 0.44



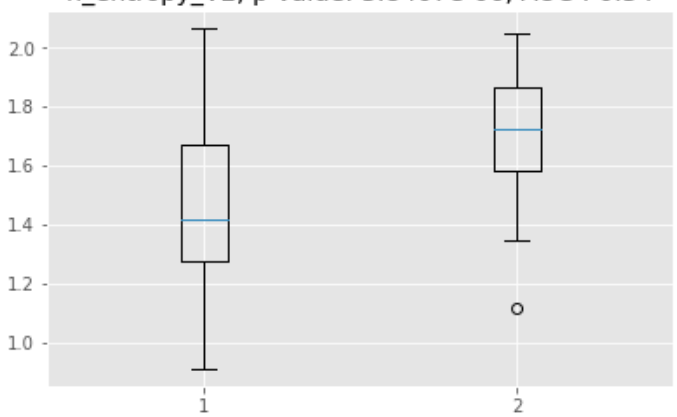
contrast_d1_A1, p-value: 6.347e-07, AUC : 0.21



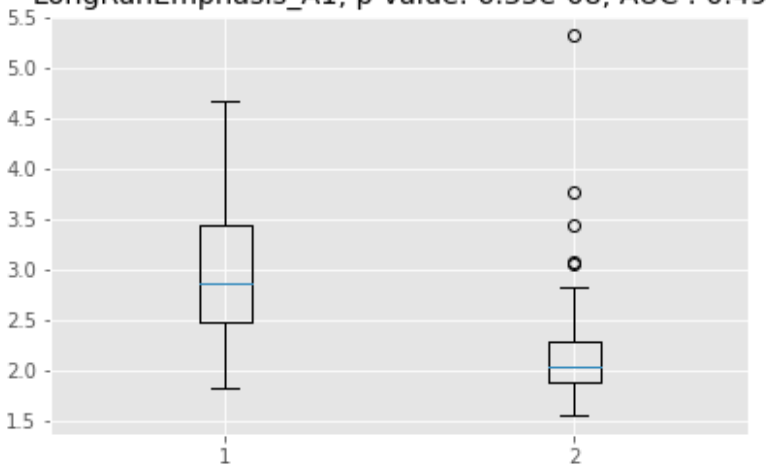
h_variance_V2, p-value: 3.979e-06, AUC : 0.23



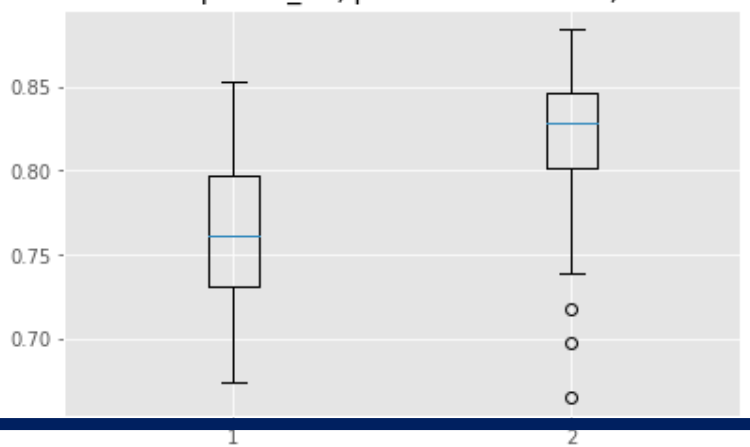
h_entropy_V2, p-value: 3.8407e-06, AUC : 0.34



LongRunEmphasis_A1, p-value: 6.35e-08, AUC : 0.49



ShortRunEmphasis_A1, p-value: 1.617e-07, AUC : 0.19



THANK YOU