



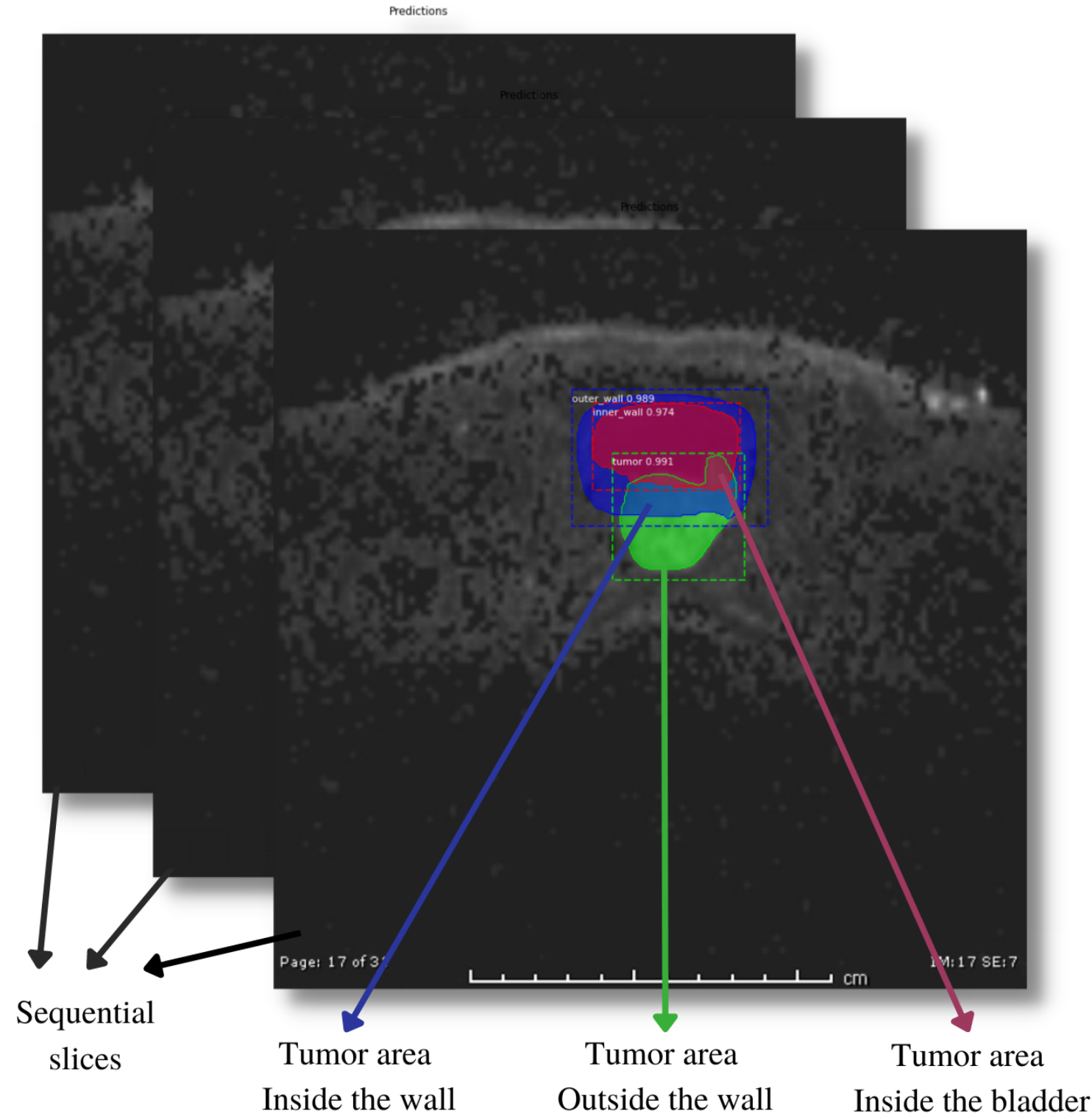
Segmentation of Bladder Lesions and Detecting Level of Invasion using Mask R-CNN

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Introduction

- Bladder Cancer is the 10th most common malignancy worldwide, with an estimated 549,000 new cases in 2018 and almost 200,000 deaths.[1]
- Multiparametric MRI (mpMRI) is a method of trying to obtain an ideal three-dimensional (3D) bladder image by combining T2-weighted (T2WI), diffusion weighted (DWI), dynamic contrast enhanced (DCEI) and, if desired, MR spectroscopy (MRSI) images.[2]
- The Vesical Imaging–Reporting and Data System (VI-RADS) is a structured reporting scheme for multiparametric bladder MRI in the evaluation of suspected bladder cancer. [3]
- MRI data of 50 patients were collected from Haseki Training and Research Hospital by obtaining FMINAREK approval.
- The main aim of this project is VIRADS scoring of bladder tumors with the help of object segmentation and machine learning classification methods.

Classification

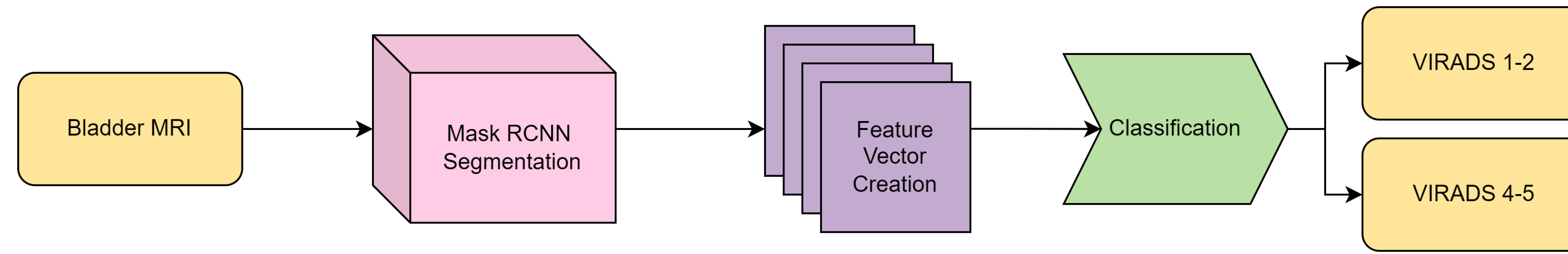


- Features are selected according to ensure the conservation of the necessary information that used in the diagnosis step by radiologists.
- Tumors expand in 3 dimensions. In order to calculate the volumetric property, areas summed up through sequential slices respectively.
- Image count may vary between patients. Therefore a variable approach was followed.
- tot : total tumor area, i_b : tumor area inside the bladder, i_w : tumor area inside the bladder wall, o : tumor area outside the bladder wall.

$$\frac{1}{\sum tot} \sum [i_w, i_b, o]$$

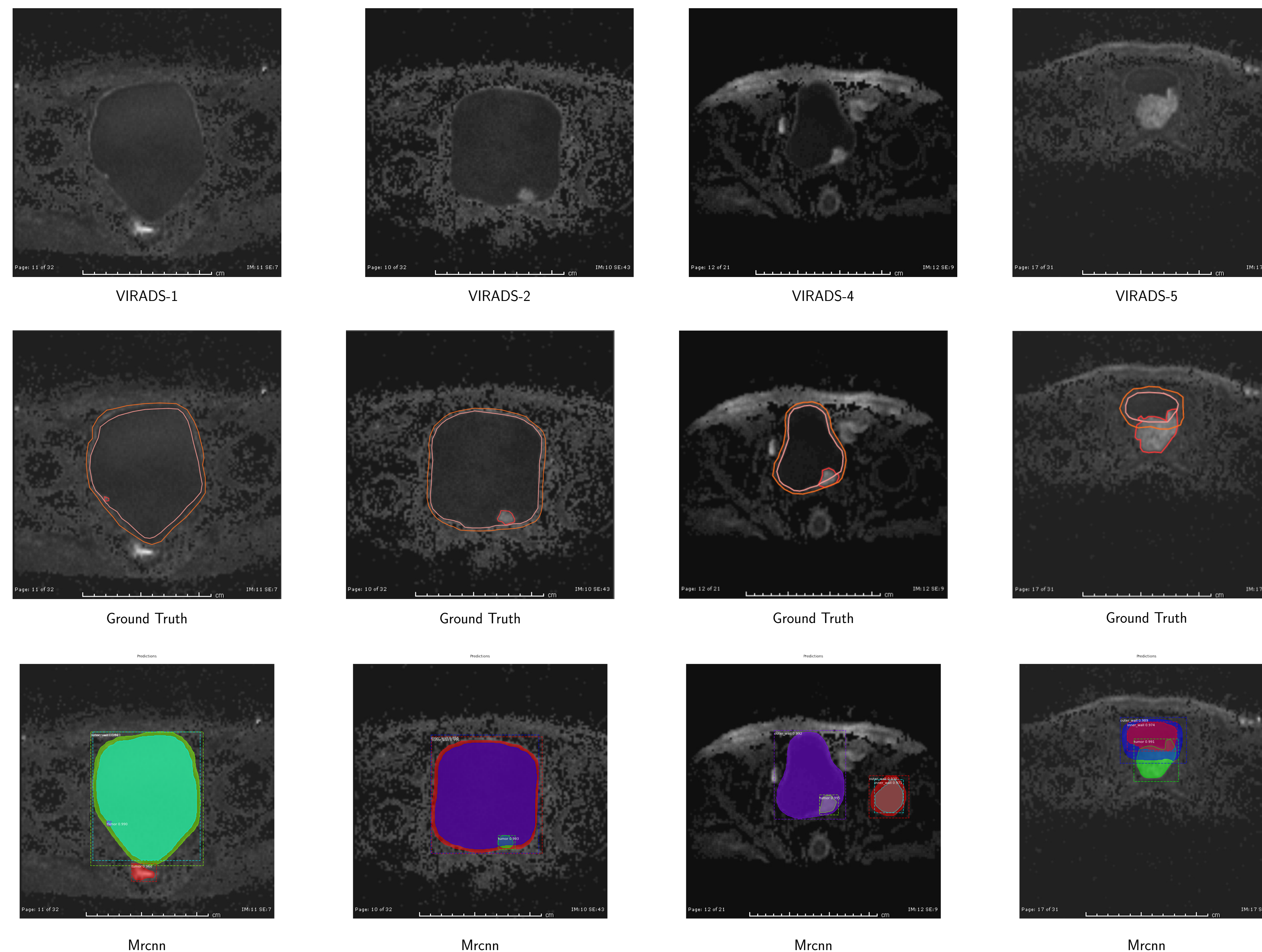
VIRADS Score	1	2	3	4	5
# of Tumors	28	25	17	4	7

Methodology



- In the first step, pretrained Mask R-CNN model fed with DWI MRI sequence.
- After getting segmented images, necessary fields are calculated and summed up to derive volumes.
- The resulting features are used with different classifiers. We implemented a rule-based unsupervised classifier which imitates the diagnosing steps of radiologists.
- In the first stage, binary classification was used to increase the success due to the small dataset. After creating a larger dataset, multiclass classification can be used.

Segmentation of DWI MRI's



Classification Results

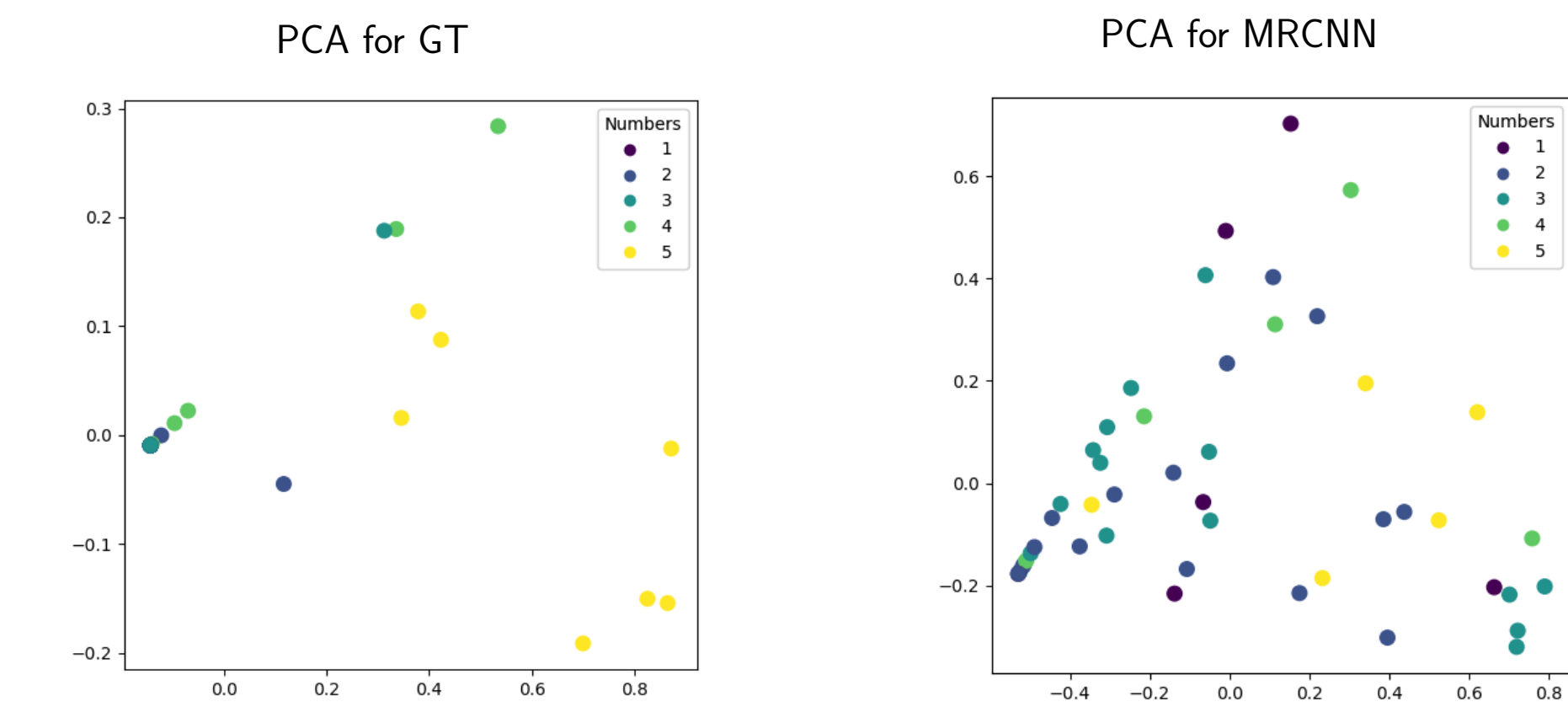


Table: Results of Ground Truth Masks

	Our Method			KNN Method			MNB Method		
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score
Virads 1-2	0.859	1.00	0.854	0.852	1.00	0.856	0.856	1.00	0.852
Virads 4-5	1.00	0.75	0.856	1.00	0.852	0.850	1.00	0.64	0.78
Microavg	0.852	0.852	0.852	0.854	0.854	0.854	0.859	0.859	0.859
Macroavg	0.855	0.858	0.851	0.856	0.851	0.853	0.853	0.852	0.857

Table: Results of Mask Rcnn Segmentation

	Our Method			KNN Method			MNB Method		
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score
Virads 1-2	0.853	0.23	0.36	0.60	0.71	0.65	0.62	0.76	0.68
Virads 4-5	0.35	0.850	0.50	0.00	0.00	0.00	0.00	0.00	0.00
Microavg	0.44	0.44	0.44	0.48	0.48	0.48	0.52	0.52	0.52
Macroavg	0.59	0.56	0.58	0.30	0.36	0.33	0.31	0.38	0.34

- Multinomial Naive Bayes, KNN and the Specific Rule-based classification algorithms tested with GT (ground truths) and MRCNN segmented images using five-fold cross-validation.
- Methods tested with ground truths (annotated by an expert) revealed successful results. However, Mask RCNN segmented images did not show success in classification.
- In the PCA plots, the ground truth dataset has obvious clusters between VIRADS 5 and VIRADS 2.
- PCA plotting of Mask RCNN is dispersed and there are no obvious clusters observed.

Conclusion

Classification strategy gave promising results in ground truths. Since we have a very limited data, the segmentation part did not satisfy the expectations. There must be more data in order to increase the accuracy of both the segmentation and classification parts.

Acknowledgement

- We would like to express our special thanks to Dr. Mustafa Orhan Nalbant and Dr. Rüşti Türkay for their precious efforts in the creation of the dataset and for sharing their knowledge.
- We are grateful to Pınar Yanardağ and Suzan Üsküdarlı for guiding us with their experiences and for the time they have devoted to us.

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