Kidney Cancer Detection from CT Images by Transformer-Based Classifiers

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Outline

- Background
- Methods
- Experimental Results
- Conclusion

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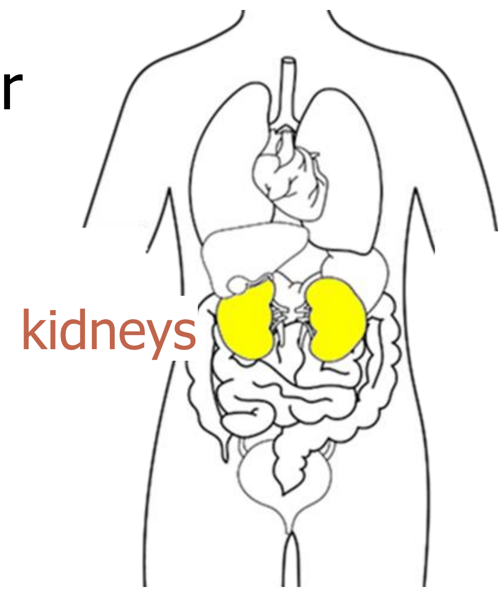
Background: Kidney Cancer Detection (1)

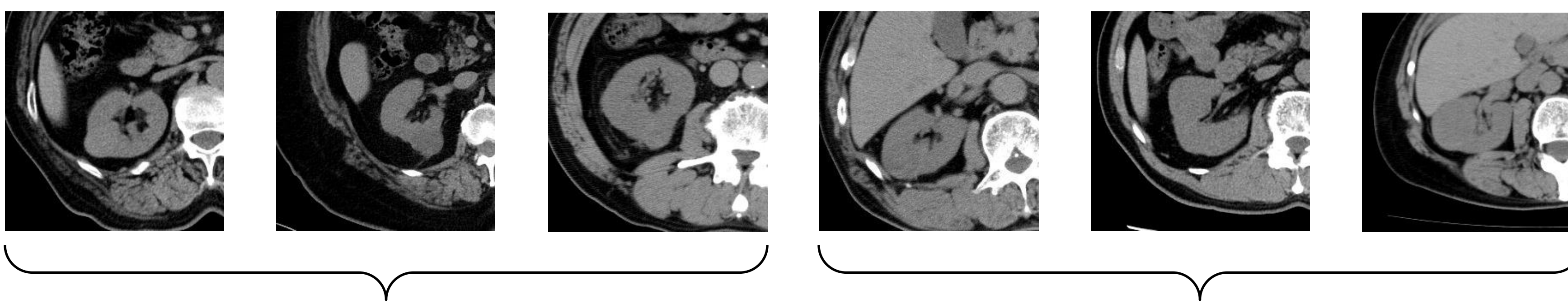
- Convolutional neural networks (CNNs) have been widely adopted in medical image analysis
- CNNs have also been applied to diagnoses on kidney cancer based on abdominal CT images:
  - Detecting kidney cancer [Hussain+ 17][Takahashi+ 20]

    Our target
  - Discriminating between benign and malignant renal masses [Oberai+ 20]
  - Identifying the subtypes of kidney cancer [Han+ 19][Uhm+ 21]



Background: Kidney Cancer Detection (2)

- Challenges:
  - Texture of cancerous tumors and normal tissues can be very similar
  - Locations of abdominal organs can vary depending on individual patients
  - Some cancerous tumors (called endophytic tumors) can grow inside kidneys



Exophytic tumors | Endophytic tumors

Background: Kidney Cancer Detection (3)

- Human experts conventionally use some substances called contrast agents to enhance the contrast among tissues

30 seconds after injecting a contrast agent to the patient

UCT (Unenhanced CT) image

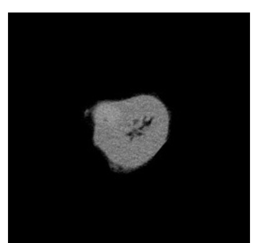
CECT (Contrast-enhanced CT) image

- Some patients have allergy to contrast agents
- Contrast agents may worsen the renal function

High clinical cost

- It was reported that masking all organs around a kidney is effective [Takahashi+ 20]

Mask



High annotation cost

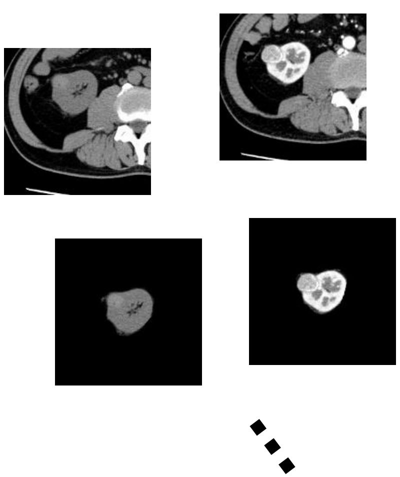
Background: Our Motivation

- In NLP and CV, Transformer-based deep neural networks have demonstrated high predictive performance

This work:

We apply transformer-based classifiers to kidney cancer detection from various types of CT images

Various types of CT images with different clinical/annotation costs



Transformer-based classifiers

Vision Transformer (ViT)
Swin Transformer

Detection:

Presence/absense of a cancerous tumor

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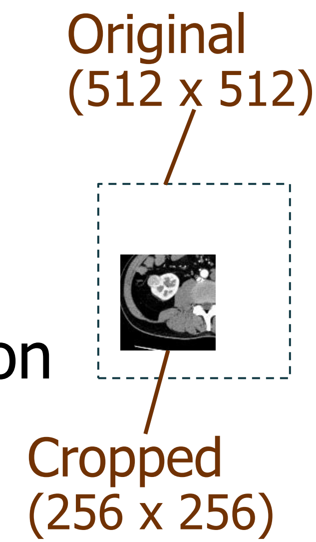
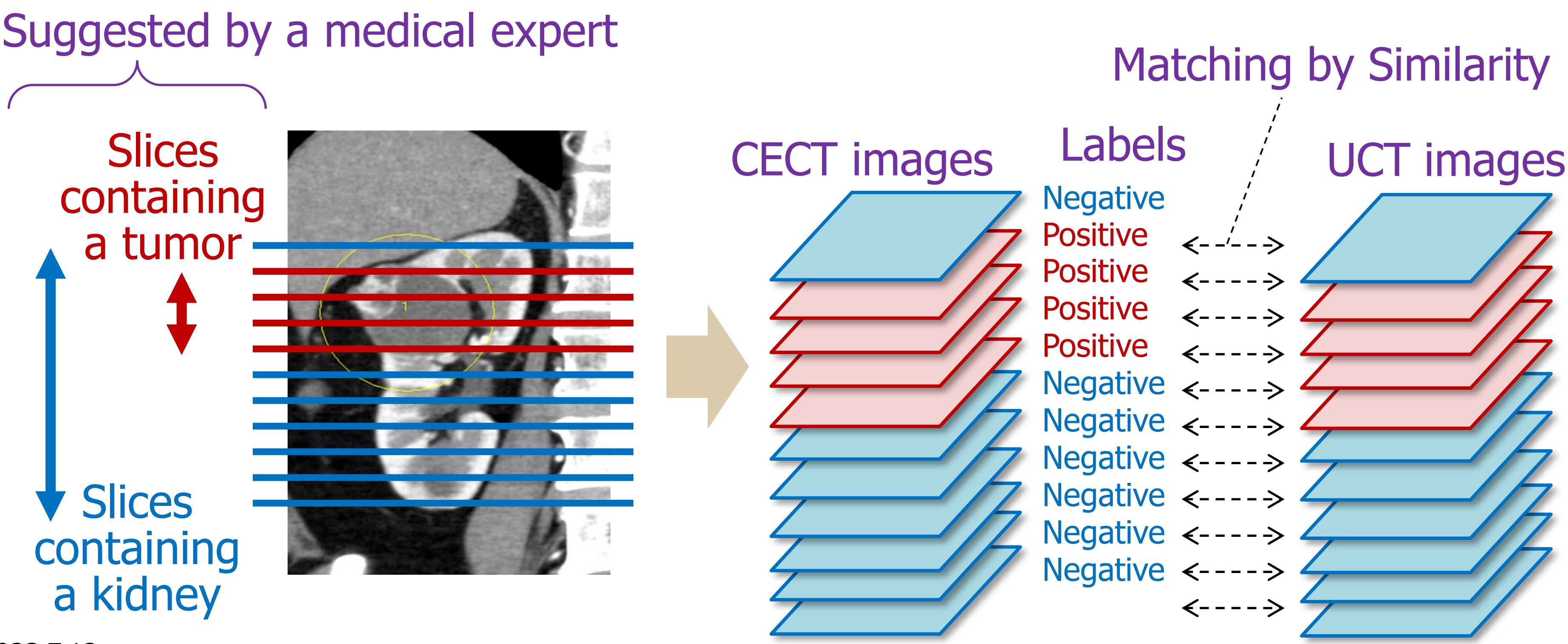
Methods: Datasets (1)

- CT values stored in DICOM-formatted files were converted into digital images
- Area of size 256 x 256 was cropped at a fixed position where the majority of kidneys were centered
- CT images were labelled as positive or negative:





Methods: Datasets (2)

- CT images containing a left kidney were horizontally flipped
  - Supposed that right and left kidneys are symmetric
  - One patient having two kidneys = Two virtual patients

- Entire dataset was split in our experiment:

Dataset	# of (virtual) patients		# of CT images	
	Present	Absent	Present	Absent
Training	148	146	728	5,212
Validation	30	30	141	1,027
Evaluation	39	40	196	1,397
Total	217	216	1,065	7,636

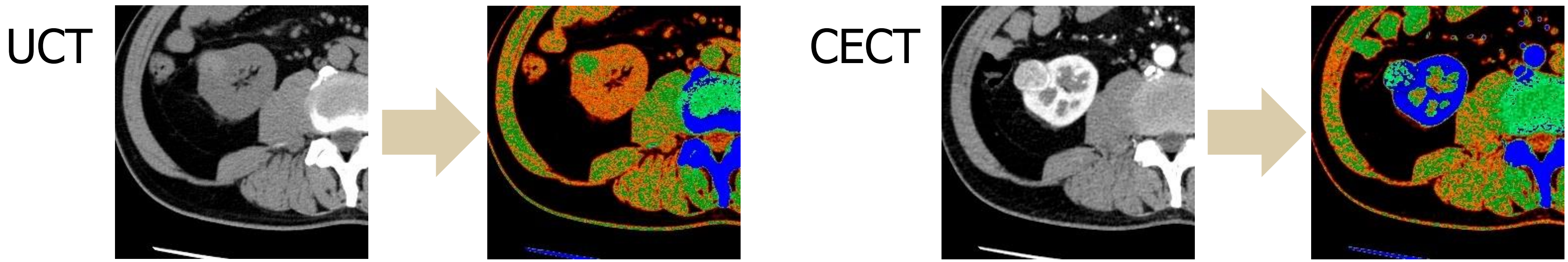
433

8,701

- Data augmentation at the beginning of each epoch
  - Shift, Rotation, Shear transformation, and Zooming-in/out

Methods: Datasets (3)

- Virtually colorized version of all CT images were created based on the CT values in the Hounsfield Unit scale

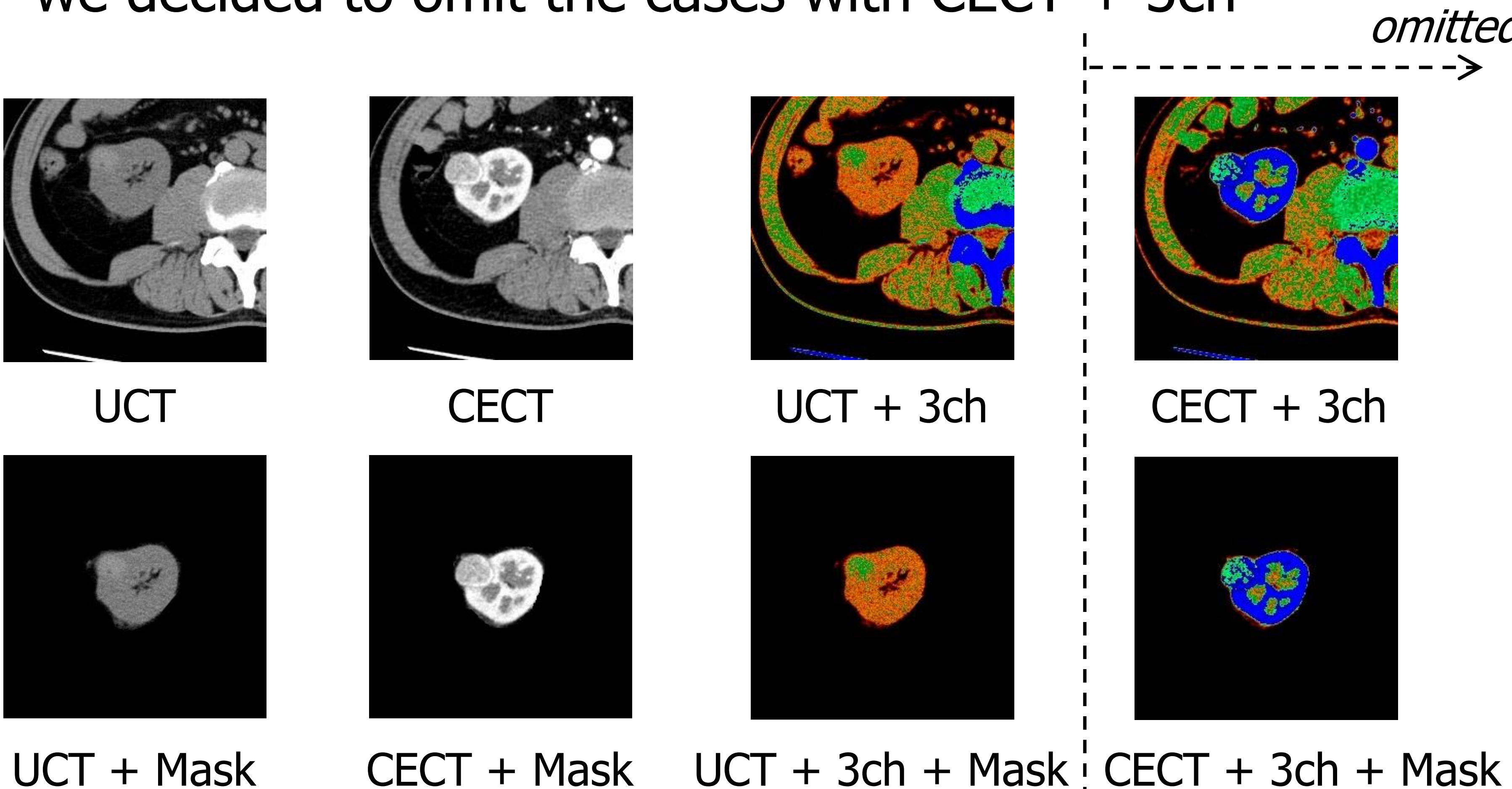


		Range of CT value (HU)	Tissue
Grayscale		−110 ~ 190	All
Virtual color (3ch) [Takeuchi+ 21]	Red	−70 ~ 50	Fat and water
	Green	−10 ~ 110	Water and soft tissue
	Blue	50 ~ 170	Soft tissue and bone

- Masked version of all CT images were created manually

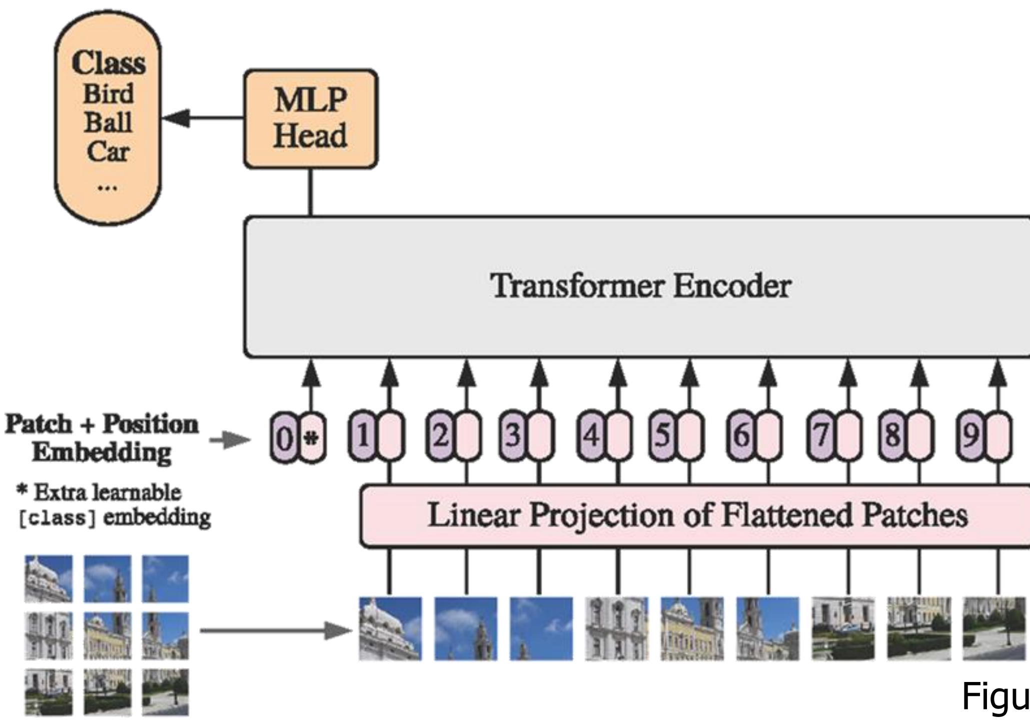
Methods: Datasets (4)

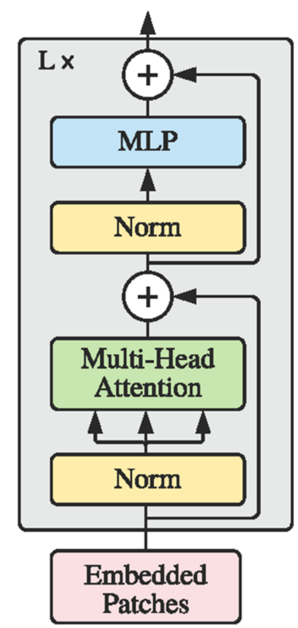
- Consequently, we can consider 8 variations of CT images with different clinical/annotation costs
- From the results of a preliminary experiment, we decided to omit the cases with CECT + 3ch



Methods: DNNs for Image Classification (2)

- Convolutional neural networks (CNNs)
  - We used VGG-16, ResNet-50
- Vision Transformer (ViT) [Dosovitskiy+ 21]
  - Uses the encoder part of the original Transformer
  - Splits an input image into patches of a fixed size
  - Applies multi-head self-attention (MSA) repeatedly
  - Can capture long-range dependency in the input image

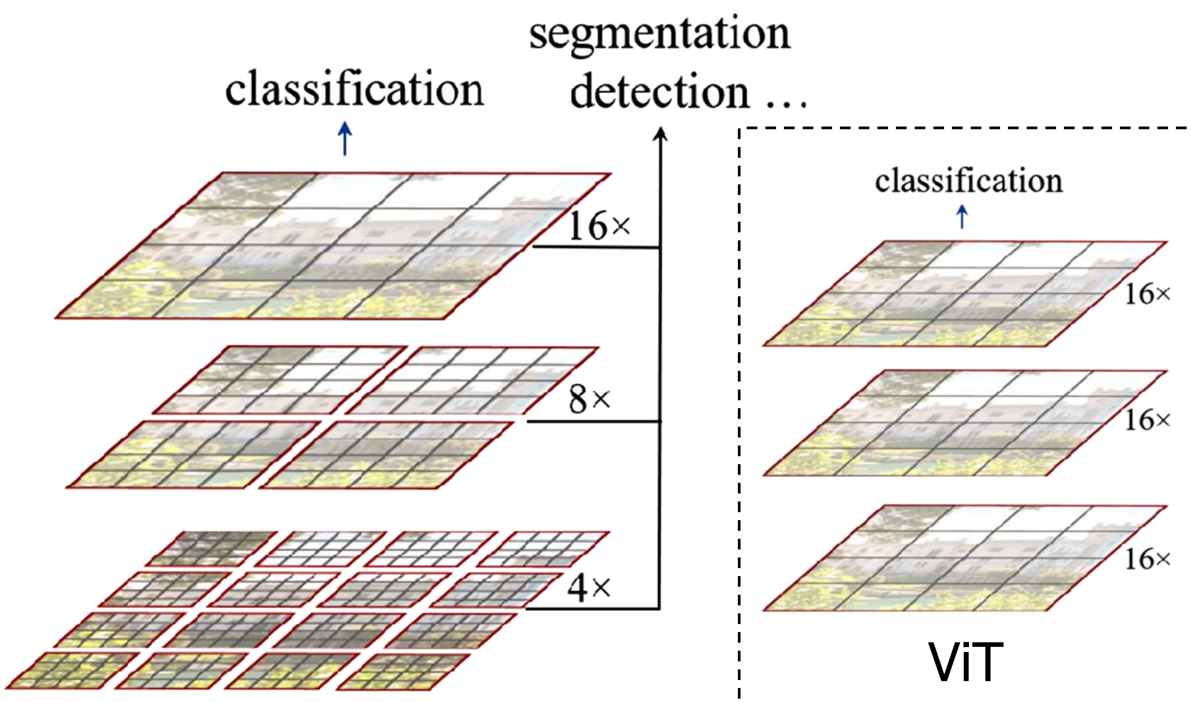




Figures excerpted from [Dosovitskiy+ 21]

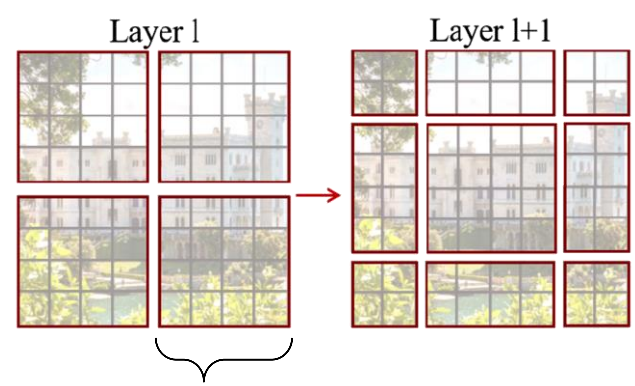
Methods: DNNs for Image Classification (3)

- Swin Transformer [Liu+ 21]
  - Inherits the basic architecture from ViT
  - Introduces a CNN-like hierarchical and local structure via patch merging
  - Performs window-based MSA (W-MSA) and shifted window-based MSA (SW-MSA) alternately



Swin Transformer

W-MSA SW-MSA

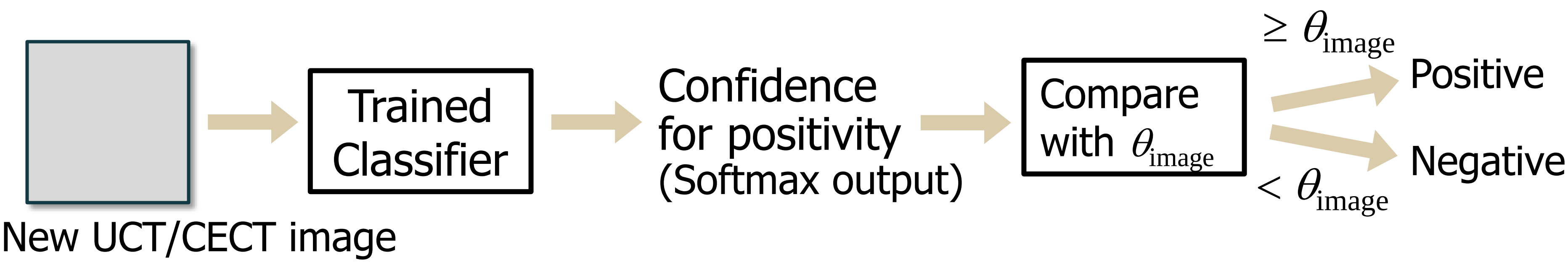


Window
= Range of a self-attention being performed

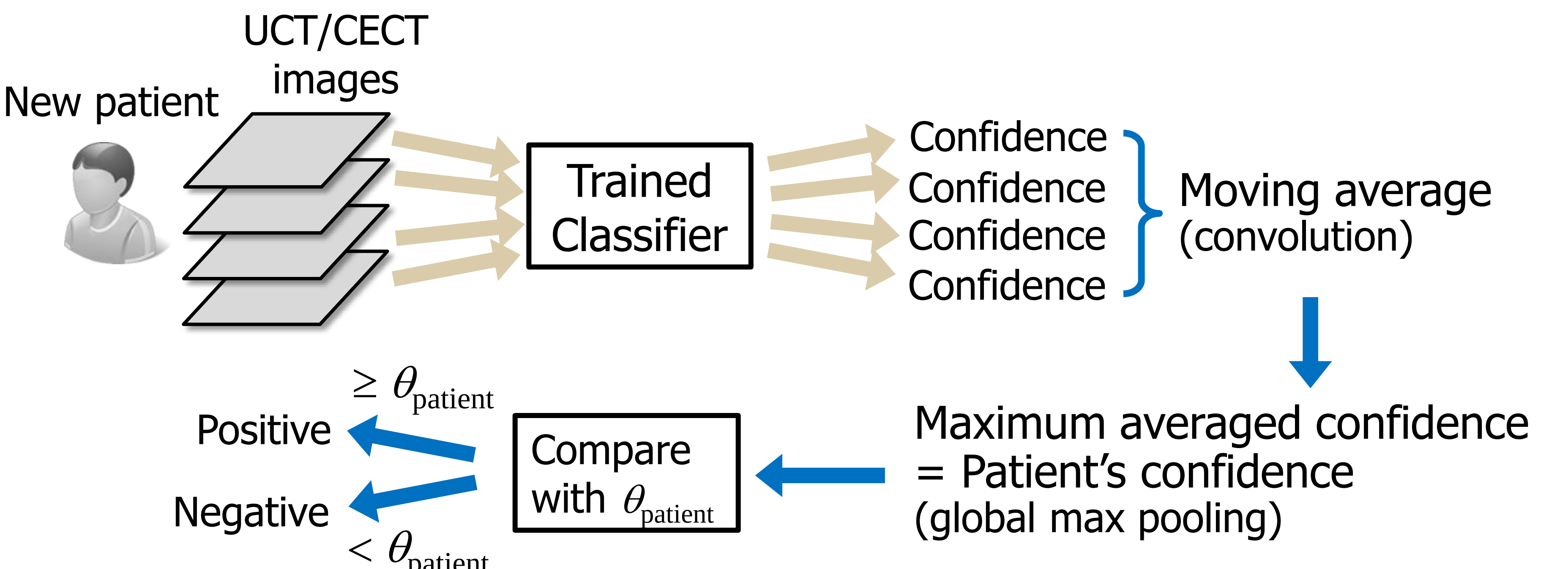
Figures excerpted from [Liu+ 21]

Methods: Image/Patient-wise Detection

- Image-wise detection



- Patient-wise detection



Methods: Configuration for Training

- Loss: Weighted cross-entropy (for coping with class imbalance)
- AdaGrad with initial learning rate of 10^{-5}
- Mini-batch size: 32
- # of epochs:
  - 150 for VGG-16/ResNet-50 with UCT images
  - 200 for VGG-16/ResNet-50 with CECT images
  - 50 for ViT
  - 100 for Swin Transformer
- Pre-trained models:
  - VGG-16 with ImageNet-1K (# of parameters: 134M)
  - ResNet-50 with ImageNet-1K (24M)
  - ViT with ImageNet-21K (303M)
  - Swin Transformer with ImageNet-21K (195M)

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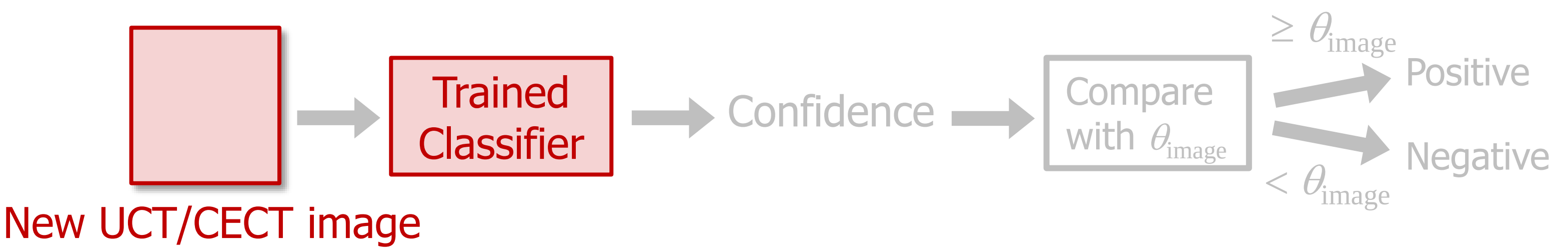
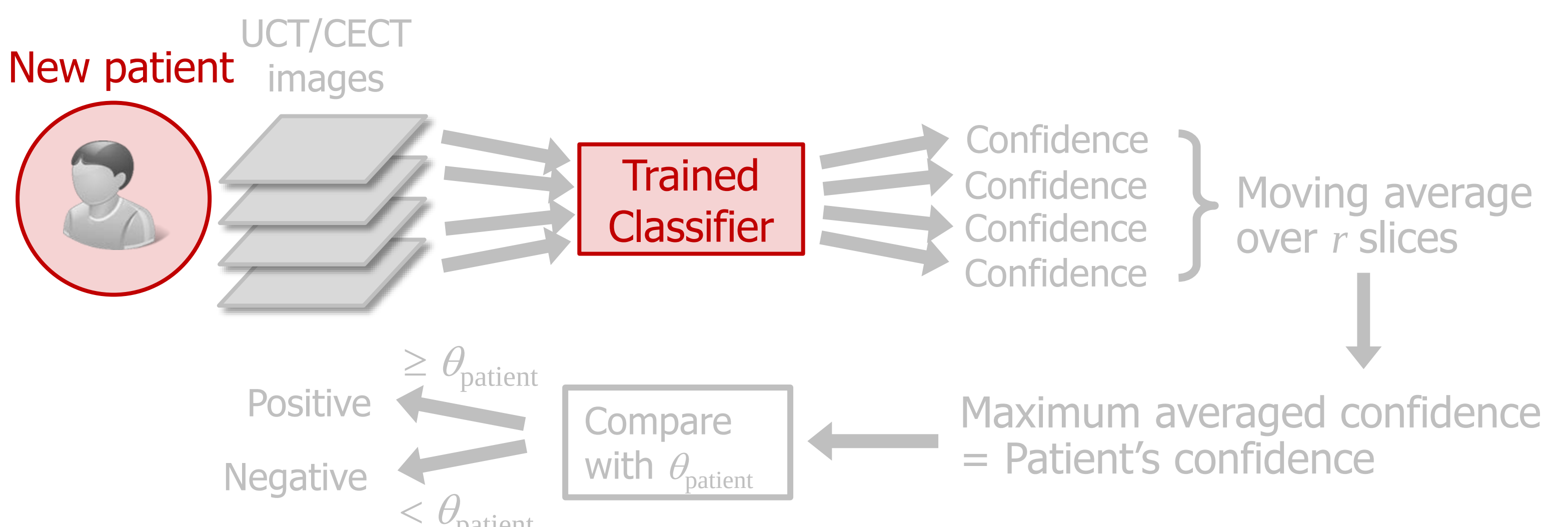
Results: Evaluation Metrics

- We evaluated classifiers using Precision, Recall, F-measure, and AUROC of:
  - Image-wise detection to evaluate the classifiers directly



  - Patient-wise detection to evaluate the classifier from a practical viewpoint



Results: Image-wise Detection

CT Images	Model	Precision	Recall	F-measure	AUROC
 UCT	VGG-16	0.374	0.174	0.237	0.679
	ResNet-50	0.280	0.398	0.328	0.713
	ViT	0.284	0.485	0.358	0.735
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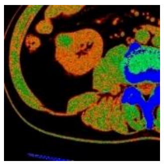 UCT + 3ch	VGG-16	0.262	0.327	0.291	0.678
	ResNet-50	0.315	0.378	0.343	0.729
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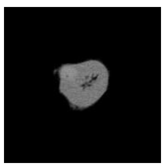 UCT + Mask	VGG-16	0.439	0.519	0.476	0.816
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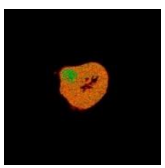 UCT + 3ch + Mask	VGG-16	0.484	0.567	0.522	0.846
	ResNet-50	0.453	0.540	0.493	0.818
	ViT	0.487	0.594	0.535	0.841
	SwinT	0.620	0.594	0.607	0.854
 CECT	VGG-16	0.500	0.464	0.482	0.818
	ResNet-50	0.528	0.538	0.529	0.823
	ViT	0.748	0.546	0.631	0.906
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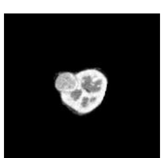 CECT + Mask	VGG-16	0.711	0.500	0.587	0.845
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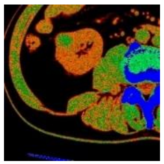
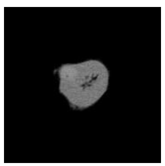
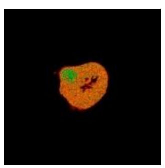
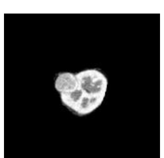
Results: Image-wise Detection



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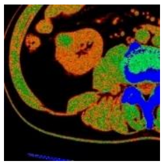
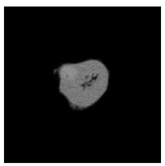
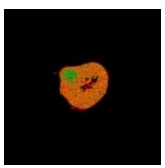
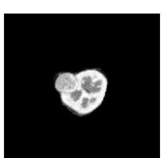
At the price of clinical costs for some patients, the accuracies for CECT images were higher than those for UCT images

Results: Image-wise Detection



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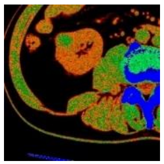 UCT + 3ch	VGG-16	0.262	0.327	0.291	0.678
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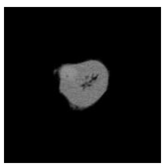 UCT + Mask	VGG-16	0.439	0.519	0.476	0.816
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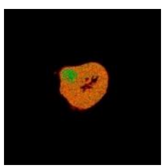 UCT + 3ch + Mask	VGG-16	0.484	0.567	0.522	0.846
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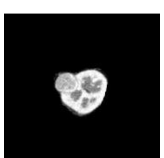 CECT + Mask	ResNet-50	0.638	0.589	0.612	0.853
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Virtual colorization of UCT images was beneficial, considering its low execution cost

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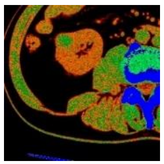	UCT + 3ch	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
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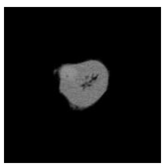	UCT + Mas[illegible]	VGG-16	0.439	0.519	0.476	0.816
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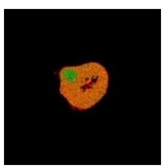
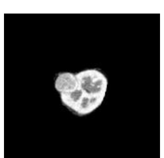
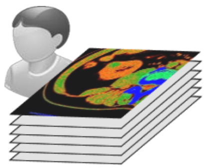
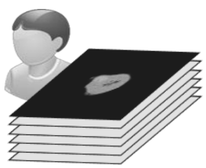
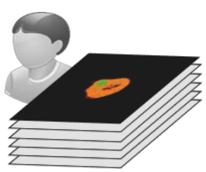
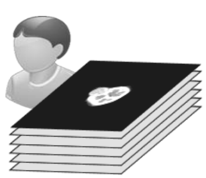
	UCT + 3ch + Mas[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	CECT	VGG-16	[illegible]	[illegible]	[illegible]	[illegible]
		ResNet-50	0.528	0.538	0.529	0.823
		ViT	0.748	0.546	0.631	0.906
		SwinT	0.855	0.480	0.614	0.901
	CECT + Mask	VGG-16	0.711	0.500	0.587	0.845
		ResNet-50	0.638	0.589	0.612	0.853
		ViT	0.754	0.672	0.711	0.926
		SwinT	0.785	0.703	0.742	0.944

Transformer-based models generally performed better than CNNs

Difference turned to be larger for CECT images

Hypothesis:
Since ViT is biased towards shape [Turi+ 21], the shape of the contrast-enhanced part might have been better captured

Results: Patient-wise Detection

CT Images	Model	Precision	Recall	F-measure	AUROC
 UCT	VGG-16	0.540	0.692	0.607	0.596
	ResNet-50	0.491	0.718	0.583	0.608
	ViT	0.514	0.949	0.667	0.671
	SwinT	0.595	0.641	0.617	0.699
 UCT + 3ch	VGG-16	0.516	0.846	0.641	0.580
	ResNet-50	0.676	0.590	0.630	0.695
	ViT	0.634	0.667	0.650	0.682
	SwinT	0.608	0.795	0.689	0.701
 UCT + Mask	VGG-16	0.714	0.769	0.741	0.801
	ResNet-50	0.725	0.744	0.734	0.843
	ViT	0.844	0.692	0.761	0.799
	SwinT	0.833	0.769	0.800	0.848
 UCT + 3ch + Mask	VGG-16	0.682	0.769	0.723	0.798
	ResNet-50	0.623	0.846	0.717	0.837
	ViT	0.721	0.795	0.756	0.811
	SwinT	0.723	0.872	0.791	0.859
 CECT	VGG-16	0.688	0.564	0.620	0.733
	ResNet-50	0.735	0.641	0.685	0.762
	ViT	0.794	0.692	0.740	0.869
	SwinT	0.933	0.718	0.812	0.899
 CECT + Mask	VGG-16	0.674	0.846	0.750	0.844
	ResNet-50	0.725	0.744	0.734	0.822
	ViT	0.731	0.974	0.835	0.940
	SwinT	0.875	0.897	0.886	0.958

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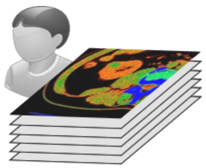 UCT + 3ch	VGG-16	0.516	0.846	0.641	0.580
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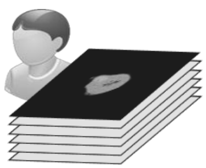 UCT + Mask	VGG-16	0.714	0.769	0.741	0.801
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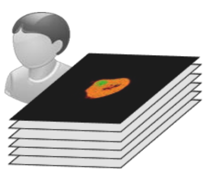 UCT + 3ch + Mask	VGG-16	0.682	0.769	0.723	0.798
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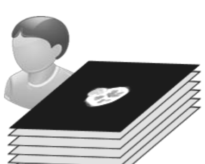 CECT + Mask	VGG-16	0.674	0.846	0.750	0.844
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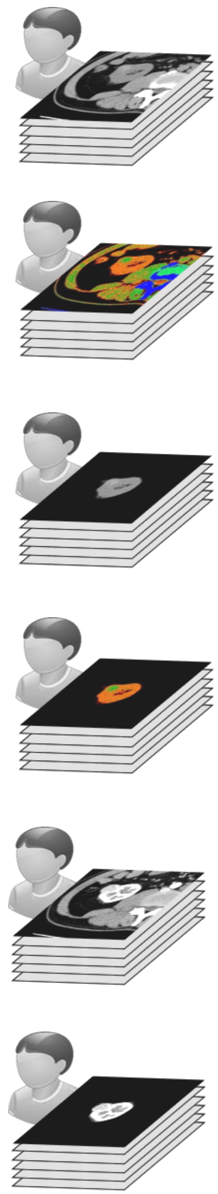
ViT did not perform better than ResNet-50 for UCT images

Results: Patient-wise Detection



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Swin Transformer generally worked the best

Outline

- ✓ Background
- ✓ Methods
- ✓ Experimental Results
- Conclusion

Conclusion

- We studied on detection of kidney cancer from CT images for 400+ (virtual) patients
- We examined CNN-based and Transformer-based classifiers (VGG-16, ResNet-50, ViT and Swin Transformer)
- We evaluated the accuracy across various types of CT images:
  - UCT images vs. CECT images
  - Masked vs. Unmasked
  - Grayscale vs. Virtually Colored
- Observations:
  - Predictive performance varied drastically depending on image types and preprocessings
  - Swin Transformer generally worked the best
  - Transformer-based models were effective especially for CECT images

Future Work

- Comparison with:
  - CNN-based models (e.g. EfficientNetV2 [Tan+ 21])
  - MLP-based models (e.g. MLP-Mixer [Tolstikhin+ 21])
  - CNN-Transformer hybrids (e.g. CvT [Wu+ 21])
- Introducing visual explanations methods (e.g. Transformer Explainability [Chefer+ 21])
- Coping with unavailability of CECT images:
  - Synthetic CECT images created by image-to-image models [Hu+ 21][Sassa+ 22]

Thank You for Your Attention!