

NEXT-GENERATION MEDICAL AI: BEYOND EXPERTS AND HYBRID ENHANCED

汇报人: 利友诚



Large-scale pancreatic cancer detection via non-contrast CT and deep learning

nature medicine

Article

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https://doi.org/10.1038/s41591-023-02640-w

"医疗AI多癌早筛公益项目"落户浙江丽水 一次平扫CT 筛查多种癌症 (大健康观察)

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Received: 9 February 2023

Accepted: 12 October 2023

Published online: 20 November 2023

Check for updates

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图为周永进正在检查患者的CT片。 阿里巴巴达摩院供图

汇报人: 利友诚

Introduction





不同排数CT检查比较								
	平扫	强化	联合强化	常规血管	心脏(冠脉)	灌注	能谱	
16排СТ	V	V		√ 图像质量较差	•		-	
64排CT	v	v	√ 小范围联合	√ 图像质量好	√ 心率70以下	√ 4cm灌注		
超高端 CT	V	V	√ 大范围联合	√ 多部位联合	√ 任意心率成像	√ 単器官灌注	V	









扫描架

基础原理很简单 X射线制造八体时、全国各种器官组织的吸收和和射发生来成

(CERES)

用記

X-1

钙化

所以,对违财过人体的X财残进行显像,我们就可获决罪能 隐器正堪和统论啦

000

感机树片

税/全保期度速 (再也不剩下说方)

友谊的小船东走

低吸收率低衰减

ALK

X-光韵相望 [6]图

吸收绝为





X线管球

工作站

机架

CT探测器



Background and Contribution



Background

Pancreatic ductal adenocarcinoma (PDAC) is **the most lethal solid malignancy**, often diagnosed at an advanced stage and unsuitable for surgery.

Early detection, early intervention.

However, due to the relatively low incidence of PDAC, effective screening in the general population requires **high sensitivity** and **specificity** to minimize the risk of overdiagnosis.

Challenge: Non-contrast computed tomography (CT) holds the potential for large-scale screening; however, the identification of PDAC using non-contrast CT has long been considered impossible, while enhanced CT is prohibitively expensive and has associated side effects on the body.

Contribution: An artificial intelligence–based system called Pancreatic Cancer Detection with Artificial Intelligence (**PANDA**) has been proposed for the detection and classification of pancreatic lesions **using non–contrast CT**. When combined with non–enhanced CT, PANDA is comparable to the use of enhanced CT in distinguishing common subtypes of pancreatic lesions.

Introduction



a

Lesion versus normal PANDA Detection PDAC PNET SPT **IPMN** Non-contrast CT Diagnosis MCN CP SCN Other Supervisions (training only) Pathology Label lesion subtypes esion and pancreas Annotation Contrast Cl masks Training set n = 3,208 from one internal center (1,431 PDAC, 839 non-PDAC, 938 normal)

Ĥ Internal test cohort n = 291 and addition cohort n = 611 (475 PDAC, 311 non-PDAC, 116 normal) **Reader studies** Assist 33 readers on non-contrast CT Compare PANDA Compare on non-contrast CT 15 readers on contrast CT ıÅ Multicenter external test n = 5,337 from 9 centers (2,737 PDAC, 932 non-PDAC, 1,668 normal) • Generalization to chest CT n = 492EÐ (63 PDAC, 51 non-PDAC, 378 normal) CLIMIC Real-world multi-scenario studies n = 20,530(chictr.org.cn, ChiCTR2200064645)

С



b





Stage 1 (Pancreas Localization):

Due to the typically small area of pancreatic lesions in CT scans, localizing the pancreas can expedite the process of lesion detection, eliminating irrelevant information and enabling focused training on the pancreatic region.

Method:

The input image size is (224, 192, 56) nnU–Net is employed for image segmentation, and the pancreatic region of the CT scan is extracted. It is then resized to a fixed size of (160, 256, 40) to enable more fine–grained classification and prediction of the CT scan.





PANDA

Stage 2 (Lesion Detection): The purpose of this stage is to detect lesions (PDAC/Non–PDAC) versus normal tissue.

Method

Using nnU–Net for further image segmentation, specifically segmenting the lesions. Additionally, multiple scale pooling layers are incorporated into the model to predict the probability of the presence of lesions.





PANDA



Stage 3 (Differential Diagnosis): The goal of the third stage is to **differentiate between different types of pancreatic Lesions**, which are classified into eight subtypes: PDAC, PNET, SPT, IPMN, MCN, chronic pancreatitis, SCN, and others. **Method:**

The image is further segmented using nnU–Net to separate the lesions into **pancreatic tissue, PDAC, and Non–PDAC regions**. Additionally, the model incorporates learnable memory tokens and learnable positional encodings for cross–layer sharing.





- 1. Lesion detection: This task involves <u>distinguishing lesions from normal tissue</u>, including detection rates based on <u>lesion type and cancer stage</u>.
- 2. Primary diagnosis: This task focuses on differentiating PDAC from non-PDAC lesions and normal tissue. It also includes evaluating PDAC identification compared to non-PDAC + normal cases.
- J Differential diagnosis: This task involves classifying PDAC and seven subtypes of non-PDAC lesions.

Evaluation



Sensitivity (敏感性), Specificity (特异性), AUC

Pred/GT		Ground	d Truth	Total		
		True	False	TOLAI		
Diagnosis	Pos.	TP	FP	prediction positive=TP+FP	PPV=TP/prediction positive, Precision	FDR=FP/prediction positive
	Neg.	FN	TN	prediction negative=FN+TN	FOR=FN/prediction positive	NPV=TN/prediction positive
合计		condition positive=TP+FN	condition negative=FP+TN	N=TP+FN+FP+TN		
		TPR=TP/condition positive, <mark>Sensitivity,</mark> Recall	FPR=FP/condition negative, 1-Specificity			
		FNR=FN/condition positive, 1-Sensitivity	TNR=TN/condition negative, Specificity			

Internal Evaluation & External Evaluation





Internal Evaluation & External Evaluation



Confusion matrix for the external validation cohort.



External evaluation centers



Identification of lesions in different lesion sbutype.



Confusion matrix for the internal validation cohort.

Internal Evaluation & External Evaluation





Reader Studies





Reader Studies





Lesion Detection on Chest CT





Lesion Detection on Chest CT





Real-World Study







Case Study





MRI report conclusion: no relapse, no metastasis

Reader Experience



					Resident 1 $(R1)$	2	4,500	300	General radiology
					Resident 2 $(R2)$	3	5,000	350	General radiology
					Resident 3 (R3)	2	1,000	200	General radiology
					Resident 4 $(R4)$	2	12,000	1,000	General radiology
Reader ID	Experience	CT read	Pancreatic CT	Traning/Expertise	Resident 5 $(R5)$	2	500	100	General radiology
Iteauer ID	(yr)	per year	read per year	Iraning/ Expertise	Resident 6 $(R6)$	4	6500	200	General radiology
Specialist 1 (S1)	17	7,500	950	Pancreatic radiology	Resident 7 (B7)	2	300	100	General radiology
Specialist 2 $(S2)$	14	3,000	550	Pancreatic radiology	$\mathbf{D}_{\text{position}} = \mathbf{P}_{\text{position}} \left(\mathbf{D}_{\text{position}} \right)$	0	12,000	250	Concercial radiology
Specialist 3 (S3)	14	15,000	1,500	Pancreatic radiology	Resident 8 (R8)	8	12,000	350	General radiology
Specialist 4 $(S4)$	7	20,000	2,000	Pancreatic radiology	Resident 9 (R9)	4	6000	200	General radiology
Specialist 5 (55)	7	12,000	460	Pancreatic radiology	Resident 10 $(R10)$	2	1200	100	General radiology
Specialist 7 (S7)	9	12,000 7500	340	Pancreatic radiology	Resident 11 (R11)	4	6000	200	General radiology
Specialist 8 $(S8)$	12	11,000	450	Pancreatic radiology	Specialist 12 (S12)	6	16.000	400	Pancreatic radiology
Specialist 9 $(S9)$	13	16,565	2600	Pancreatic radiology	Specialist 13 (S13)	7	17 000	400	Pancreatic radiology
Specialist 10 (S10)	8	15,000	560	Pancreatic radiology	Specialist 14 $(S14)$	7	15,000	500	Demonsation and islam
Specialist 11 (S11)	8	8000	1000	Pancreatic radiology	Specialist 14 (S14)	1	15,000	500	Pancreatic radiology
General 1 (G1) $$	13	3,000	150	General radiology	Specialist 15 $(S15)$	12	17,000	2,000	Pancreatic radiology
General 2 (G2) $G_{\rm C}$	31	5,000	300	General radiology	Specialist 16 (S16)	8	25,000	500	Pancreatic radiology
General 3 (G3) General 4 (G4)	9	13,000	200	General radiology	Specialist 17 (S17)	10	17.000	1.000	Pancreatic radiology
General 5 $(G5)$	8	1.800	100	General radiology	Specialist 18 (S18)	6	23,000	500	Pancreatic radiology
General 6 (G6)	8	20,000	500	General radiology	Specialist 19 (S19)	12	20,000	2,000	Pancreatic radiology
General 7 $(G7)$	8	1500	100	General radiology	Specialist 10 (S10)	12	20,000	2,000	Demensetie ne dielem
General 8 $(G8)$	10	$15,\!000$	300	General radiology	Specialist 20 (S20)	12	30,000	3,000	Pancreatic radiology
General 9 $(G9)$	9	3200	150	General radiology	Specialist 21 $(S21)$	6	17,000	400	Pancreatic radiology
General 10 $(G10)$	10	18,000	200	General radiology	Specialist 22 $(S22)$	7	15,000	1,000	Pancreatic radiology
General 11 (G11)	9	3000	150	General radiology	Specialist 23 (S23)	19	20,000	450	Pancreatic radiology
					Specialist 24 (S24)	10	20,000	450	Pancreatic radiology
					Specialist 25 (S25)	10	20,000	500	Pancreatic radiology
					Specialist 26 (S26)	10	21.000	500	Pancreatic radiology



The good generalizability of PANDA can be attributed to the following factors:

- 1. Training data from large tertiary hospitals, covering **diverse representations** of the Chinese population.
- 2. Non-contrast CT scans may be more universal for AI models compared to contrast-enhanced CT scans.
- Integration of segmentation (capturing local pathological basis) and classification reduces the risk of overfitting in pure classification-based AI models.
- 4. The model was fine-tuned to achieve reliable control of false positives, with a specificity of 99% in the cross-validation process on a large training set (n=3,208).
- 5. Specificity was further improved to 99.9% by fine-tuning on false positives from external centers and the real world (tune on RW1 and val on RW2).
- 6 Regarding training data, **similar CT imaging protocols (e.g., slice thickness, CT dose index, oral contrast)** were used for cases and controls, forcing the model to focus on the primary learning objectives rather than fitting shortcuts or confounding factors.



Al-based pathology predicts origins for cancers of unknown primary

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Article Published: 05 May 2021

AI-based pathology predicts origins for cancers of unknown primary

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Nature 594, 106–110 (2021) Cite this article

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- 1. The site of a primary tumor is crucial for guiding clinical care in metastatic cancer cases.
- 2. Determining the site of origin is challenging despite histopathological examination and clinical/radiological assessments.
- 3. Cancers categorized as CUPs (Cancer of Unknown Primary) account for 1–2% and lack a definitive primary origin.
- 4. Comprehensive diagnostic work-ups are performed for CUP patients, but empirical chemotherapy is usually administered due to the lack of primary site identification.
- 5. Genomics and transcriptomics have been proposed to identify the primary origin, but molecular profiling is not routinely conducted, especially in low-resource settings.
- 6. Uncertainty in classifying tumors as primary or metastatic and misdiagnosing relapse are reported in the literature.

TOAD workflow





Results









北京大学 PEKING UNIVERSIT

收記へ



Resaerch

Al assist Human Doctors > Al and Human Doctors





