



# Foundation Ark: Accruing and Reusing Knowledge for Superior and Robust Performance

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All code and pretrained models released

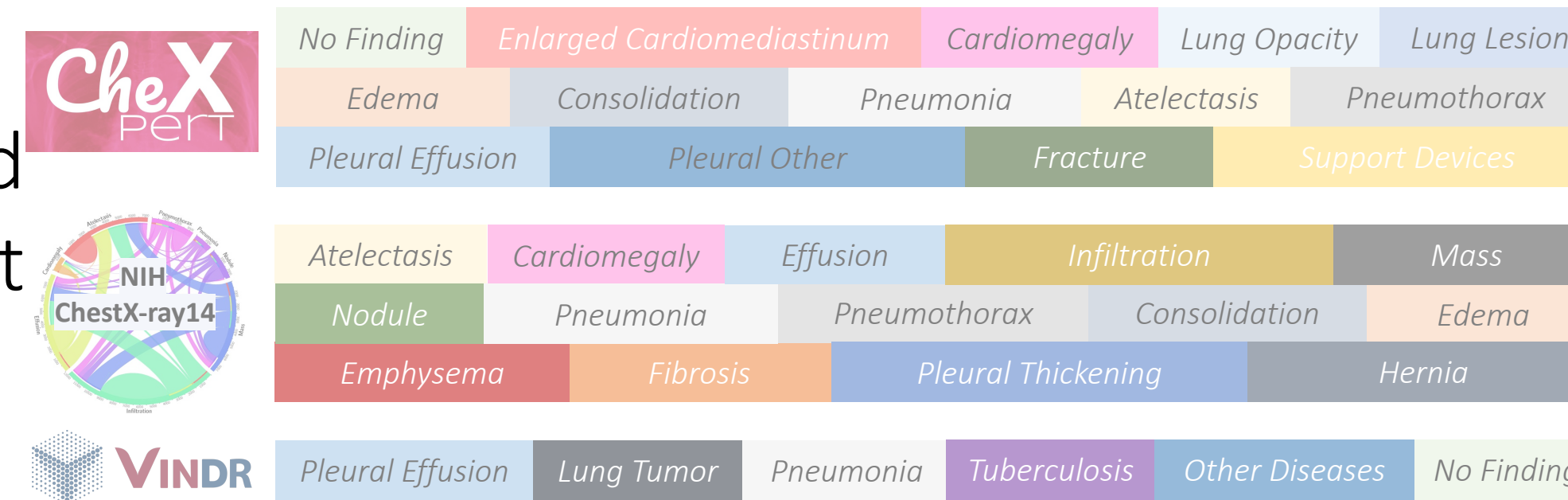
Project Page

**Background:** Achieving expert-level performance by deep learning demands massive annotated data for training. Google CXR-FM (Foundation Model) was trained with 821,544 *labeled* chest X-rays.

**Motivation:** Numerous datasets are available in medical imaging but individually small and *heterogeneous* in expert annotations. Aggregating public datasets costs nearly nothing but enlarges data size, diversifies patient populations and accrues knowledge from diverse experts.

**Vision:** Powerful and robust Foundation Models trained from numerous public (small or big) datasets. We develop open Foundation Models from numerous public datasets using their heterogeneous expert annotations

## Challenge: Label Heterogeneity



Ark trains **foundation models** with numerous public datasets by **Accruing** knowledge (from heterogeneous labels)

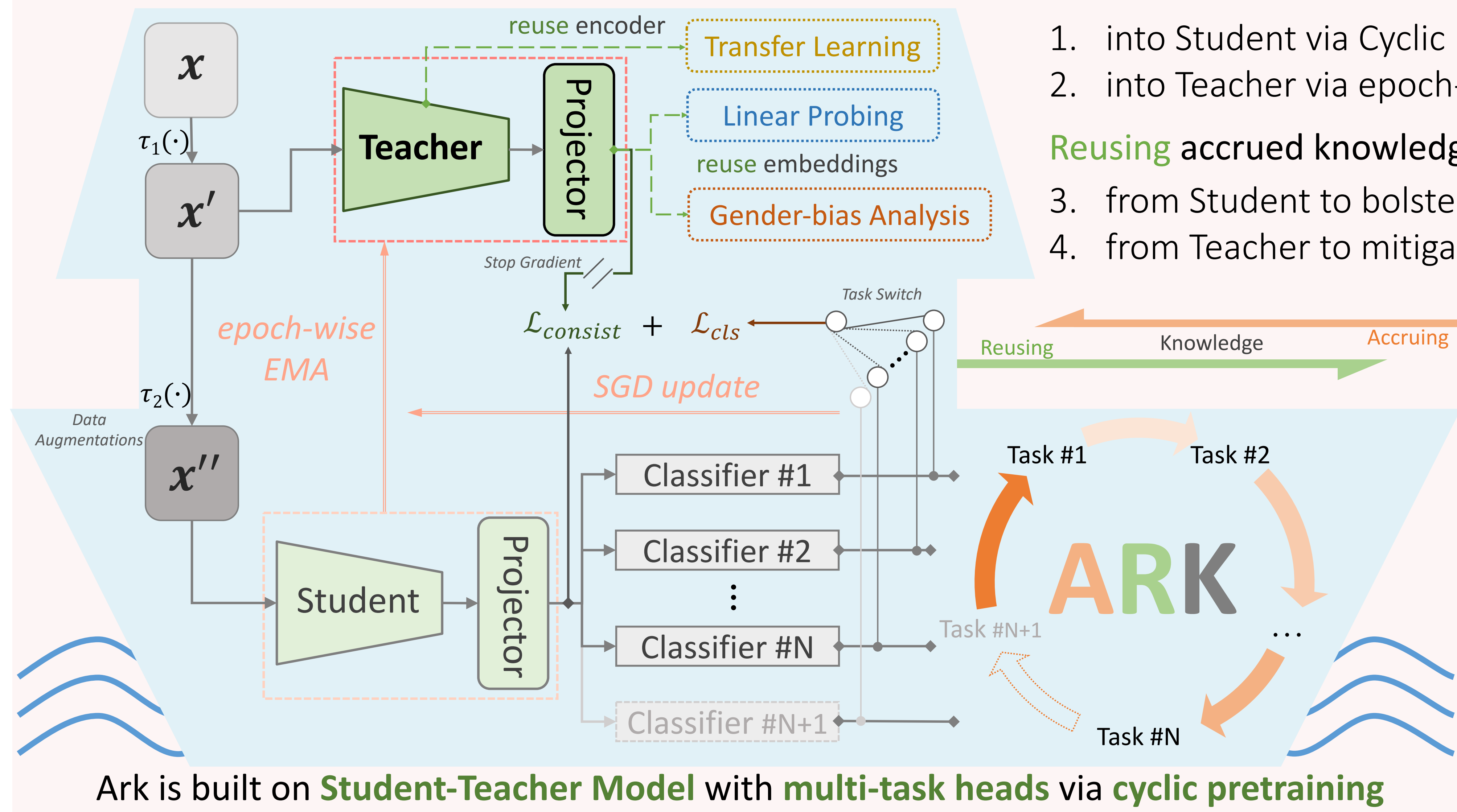
- into Student via Cyclic Pretraining
- into Teacher via epoch-wise EMA

### Reusing accrued knowledge

- from Student to bolster cyclic pretraining
- from Teacher to mitigate forgetting

### Properties of Ark:

- Knowledge-centric
- Label-agnostic
- Task-scalable
- Annotation-heterogeneous
- Application-versatile



Ark is built on **Student-Teacher Model** with **multi-task heads** via **cyclic pretraining**

Code	Task	Usage*
1.CXPT	14 thoracic diagnoses classification	P F L B
2.NIHC	14 thoracic diseases classification	P F L B
3.RSNA	Lung opacity, abnormality classification	P F L
4.VINC	6 thoracic diagnoses classification	P F L
5.NIHS	Tuberculosis classification	P F L
6.MMIC	14 thoracic diagnoses classification	P
7.NIHM	Lungs segmentation	F
8.JSRT	Lungs, heart, clavicles segmentation	F
9.VINR	20 ribs segmentation	F
10.SIIM	Pneumothorax classification	L

\* The usage of each dataset in our experiments is denoted with P for pretraining, F for finetuning, L for linear probing, and B for bias study.

**Ark's performance is inspiring:** It encourages researchers to share codes and datasets for creating open foundation models, accelerating open science, democratizing deep learning for imaging

### Result 1: Ark outperforms SOTA fully/self-supervised methods on various thoracic disease classification tasks

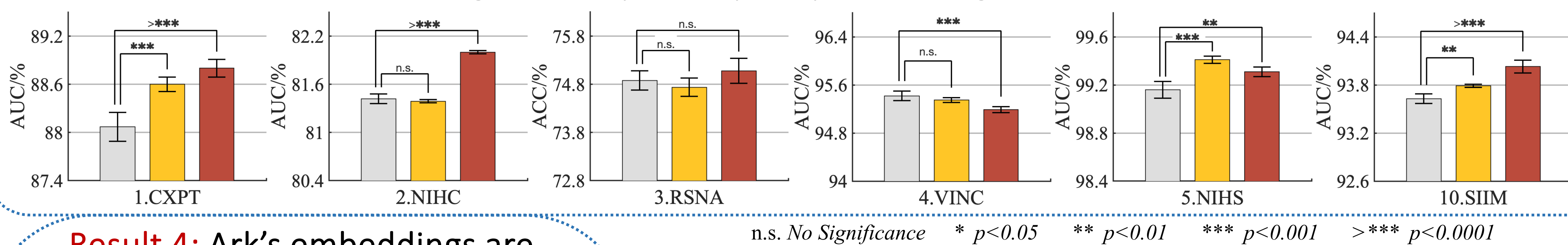
Initialization	Pretraining	1.CXPT	2.NIHC	3.RSNA	4.VINC	5.NIHS
Random	-	83.39±0.84	77.04±0.34	70.02±0.42	78.49±1.00	92.52±4.98
Supervised	ImageNet	87.80±0.42	81.73±0.14	73.44±0.46	90.35±0.31	93.35±0.77
SimMIM	ImageNet	88.16±0.31	81.95±0.15	73.66±0.34	90.24±0.35	94.12±0.96
SimMIM	IN-->CXR (926K)	88.37±0.40	<u>83.04±0.15</u>	74.09±0.39	91.71±1.04	95.76±1.79
Ark-5	IN-->CXR (335K)	88.73±0.20	82.87±0.13	<u>74.73±0.59</u>	<u>94.67±0.33</u>	<u>98.92±0.21</u>
Ark-6	IN-->CXR (704K)	<u>89.14±0.22</u>	<u>83.05±0.09</u>	<u>74.76±0.35</u>	<u>95.07±0.16</u>	<u>98.99±0.16</u>

### Result 2: Ark provides generalizable representations for organ/bones segmentation tasks

7.NIHM	8.JSRT Lung	8.JSRT Heart	8.JSRT Clavicle	9.VINR
96.32±0.18	96.32±0.10	92.35±0.20	85.56±0.71	56.46±0.62
97.23±0.09	97.13±0.07	92.58±0.29	86.94±0.69	62.40±0.80
97.12±0.14	96.90±0.08	93.53±0.11	87.18±0.63	61.64±0.69
97.10±0.40	96.93±0.12	93.75±0.36	88.87±1.06	63.46±0.89
<u>97.65±0.17</u>	<u>97.41±0.04</u>	<u>94.16±0.66</u>	<u>90.01±0.35</u>	<u>63.96±0.30</u>
<u>97.68±0.03</u>	<u>97.48±0.08</u>	<u>94.62±0.16</u>	<u>90.05±0.15</u>	<u>63.70±0.23</u>

With the best bolded and the second best underlined, a statistical analysis is conducted between the best vs. others, where green-highlighted boxes indicate no statistically significant difference at level  $p = 0.05$ .

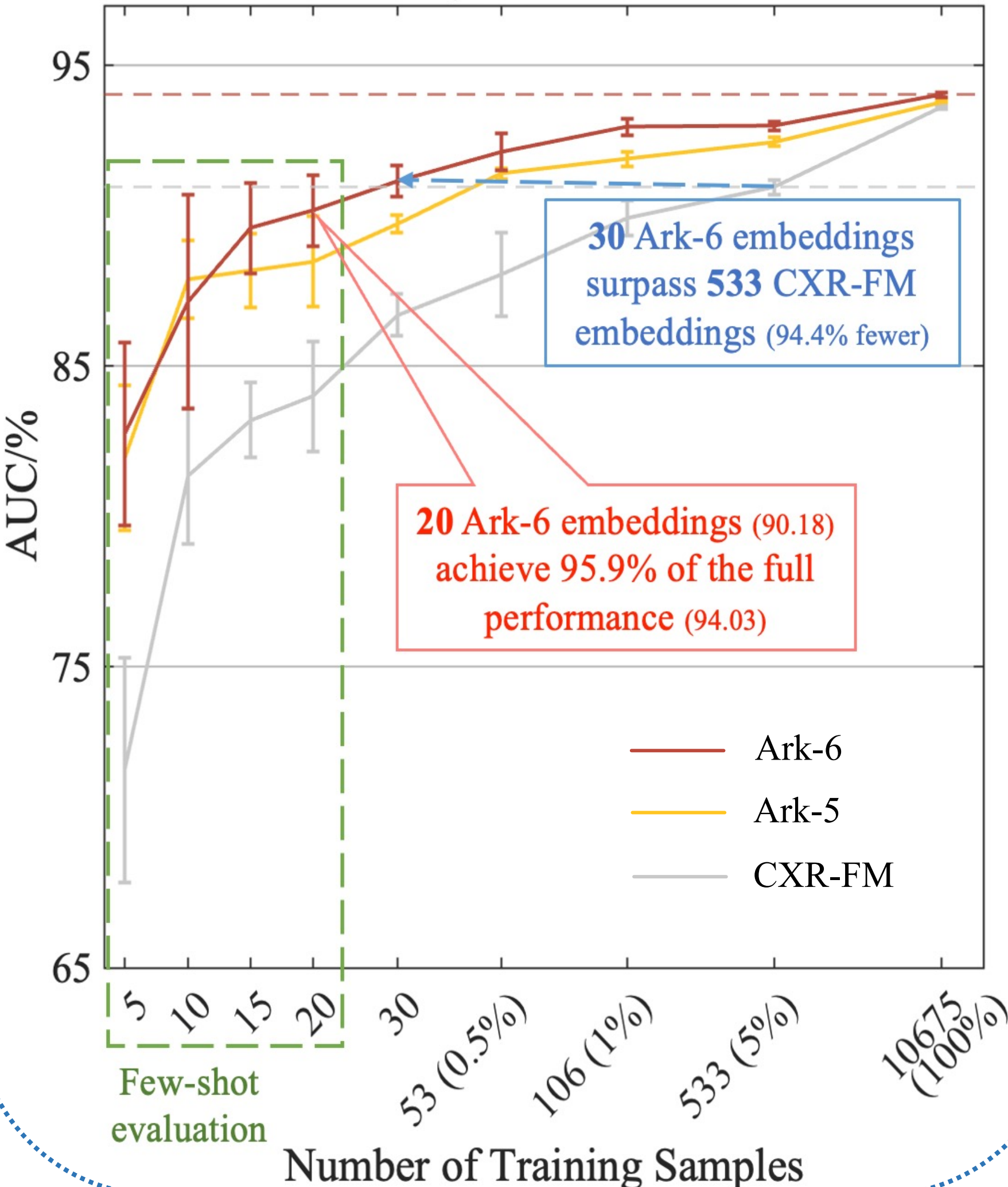
### Result 3: Ark offers embeddings with superior quality over Google CXR-FM



n.s. No Significance \*  $p < 0.05$  \*\*  $p < 0.01$  \*\*\*  $p < 0.001$  >\*\*\*  $p < 0.0001$

### Result 4: Ark's embeddings are outstanding in small data regime

#### Data Efficiency Evaluation on 10.SIIM

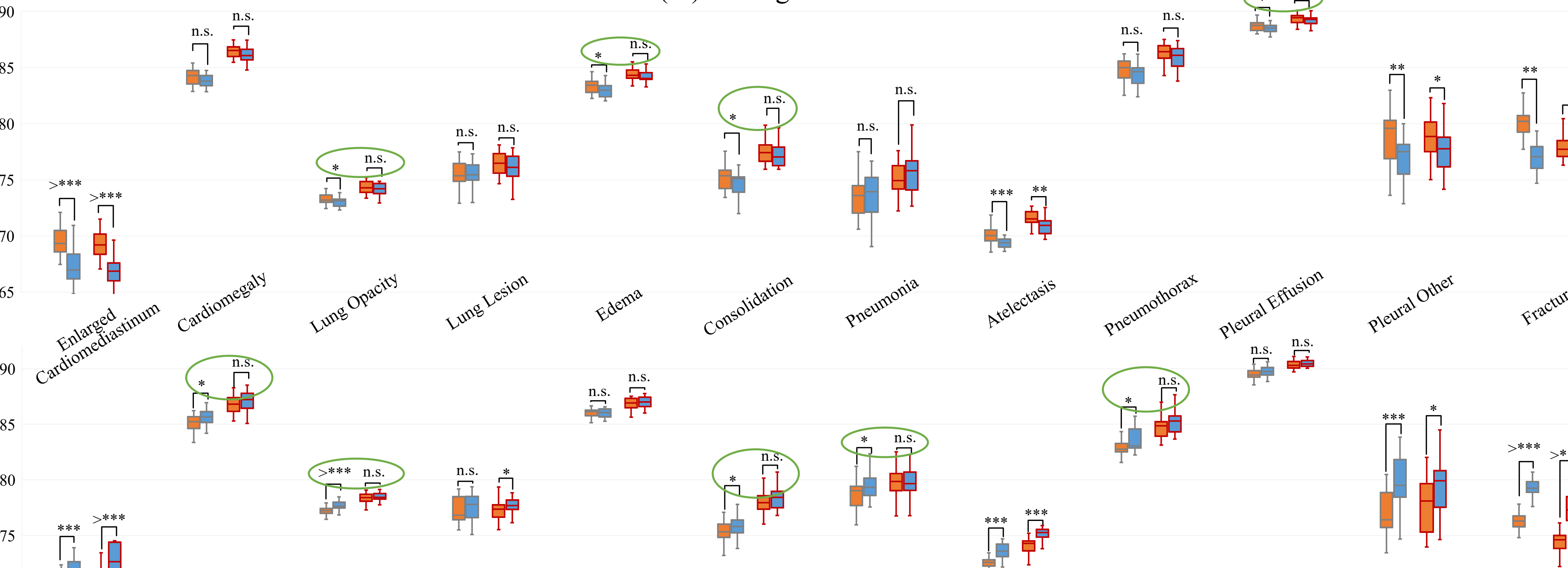


### Result 6: Ark demonstrates strong resilience to gender-biased data

Training fold for 1.CXPT (w/ embeddings from)

Female (CXR-FM) Male (CXR-FM)  
Female (Ark-6) Male (Ark-6)

AUC (%) Testing in Female Patients



AUC (%) Testing in Male Patients

Gender bias is characterized by a significant drop in performance when training and test data are of the opposite gender, compared to when they are of the same gender. Each green circle indicates a lung disease with gender bias by CXR-FM, while Ark exhibits a more robust performance, showing no significant difference.

### Result 5: Ark models show low false-negative rate

