

**Team 11-4: The GEMs**



# Embedding Model for CXR

 **or**  **for reducing bias ?**

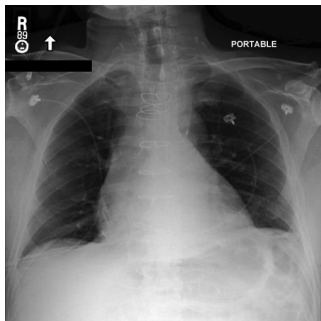
Emory Health Datathon



## Large End-to-end Task-specific Model

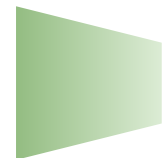
### → Predict Pathology

- Need large training set
- Require computational resource
- More overhead for data transfer



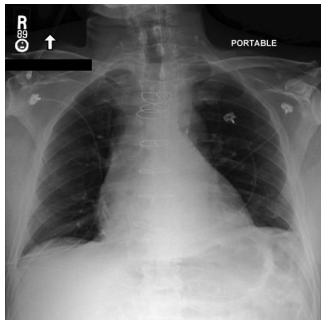
## Foundation Model

### Embedding



### Predict Pathology

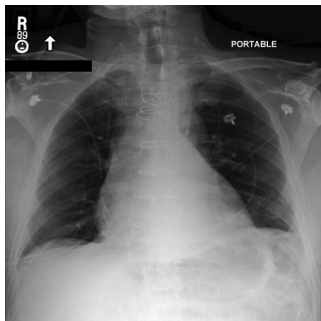
- Smaller training set
- Small model (LR, SVM, MLP, ...)
- Easier data transfer



### Large End-to-end Task-specific Model

#### → Predict Pathology

- Need large training set
- Require computational resource
- More overhead for data transfer



### Foundation Model

Access via online API

#### Embedding



#### → Predict Pathology

- Smaller training set
- Smaller model (LR, SVM, MLP, ...)
- Easier data transfer

## Advantages of Foundation Model Embedding

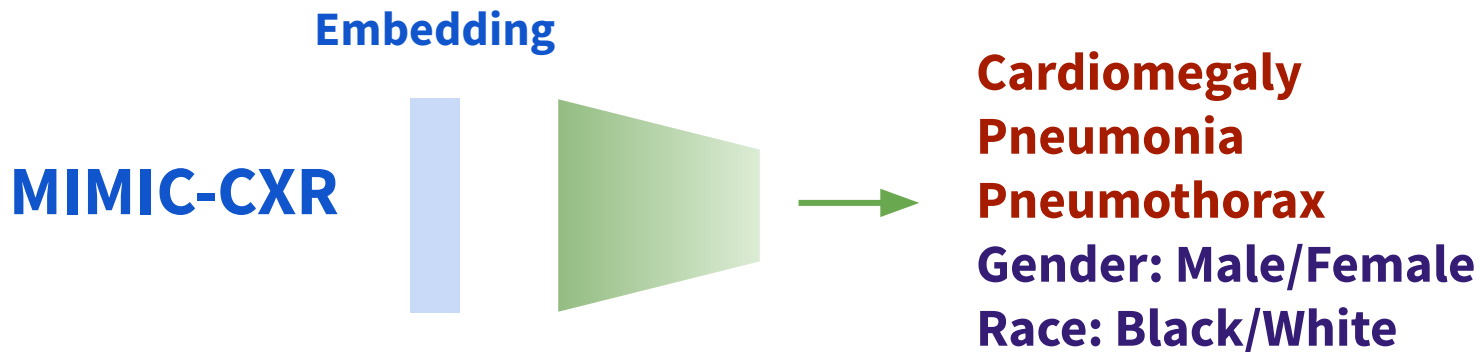
- ▷ **Smaller dataset** - good for rare pathologies and limited expert annotation
- ▷ **Smaller model** - faster to build, less computation and energy consumption
- ▷ **Easier data transfer** - facilitates collaboration
- ▷ **Better accessibility to AI - promote equity in data and computational resource**

But, is it **good** or **bad** for reducing bias ?

# Experiments

1. CXR embedding predict findings
  - ▶ Standard approach plus **subgroup analysis**
  - ▶ **Performance gap exists ?**
2. CXR embedding predict findings
  - ▶ For gender/race, **train/val on group1, test on group2**
  - ▶ **Need better balancing ?**
3. CXR embedding → **group 1** or **group 2**
  - ▶ Direct **prediction of gender/race**
  - ▶ **Potential spurious correlation ?**

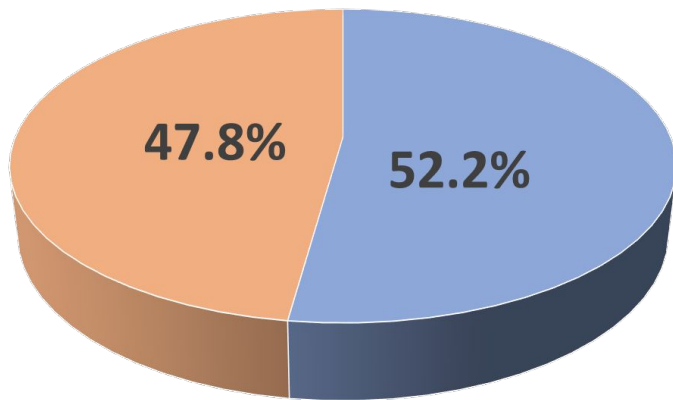
# Dataset and Model



- Input 1376, 2 hidden layer MLP (512, 256)
- Binary classifier
- Time: testing 0.0002s/image, training time is 7.5 minutes (10 epochs) on A10G GPU

## MIMIC-CXR

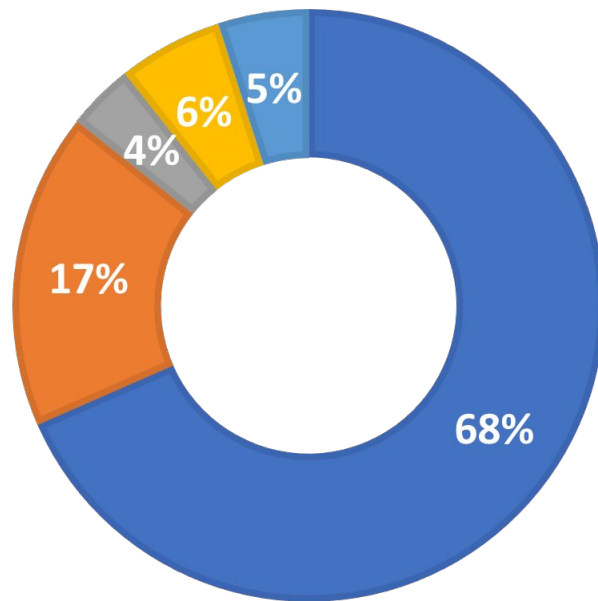
GENDER



■ Females ■ Males

RACE/ETHNICITY

■ White ■ Black ■ Asian ■ Hispanic ■ Other



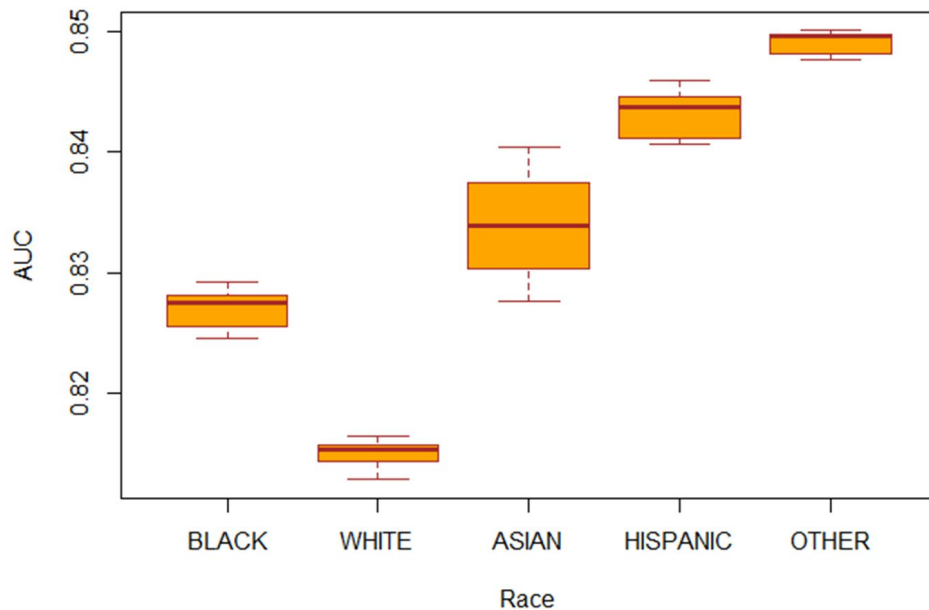


# Experiments

1. CXR embedding predict findings
  - ▶ Standard approach plus **subgroup analysis**
  - ▶ **Performance gap exists ?**
2. CXR embedding predict findings
  - ▶ For gender/race, **train/val on group1, test on group2**
  - ▶ **Need better balancing ?**
3. CXR embedding → **group 1 or group 2**
  - ▶ Direct **prediction of gender/race**
  - ▶ **Potential spurious correlation ?**

# Exp. 1: CXR→Findings, **Subgroup Analysis**

## Cardiomegaly

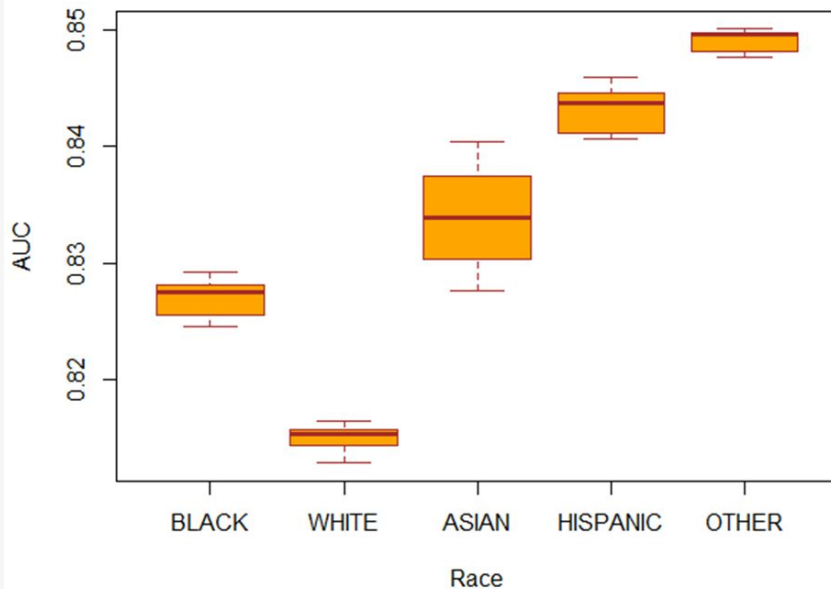


**Similar to  
Biocomputing  
2021  
TPR for Black >  
TPR for White**

**AUC for Black > AUC for White**

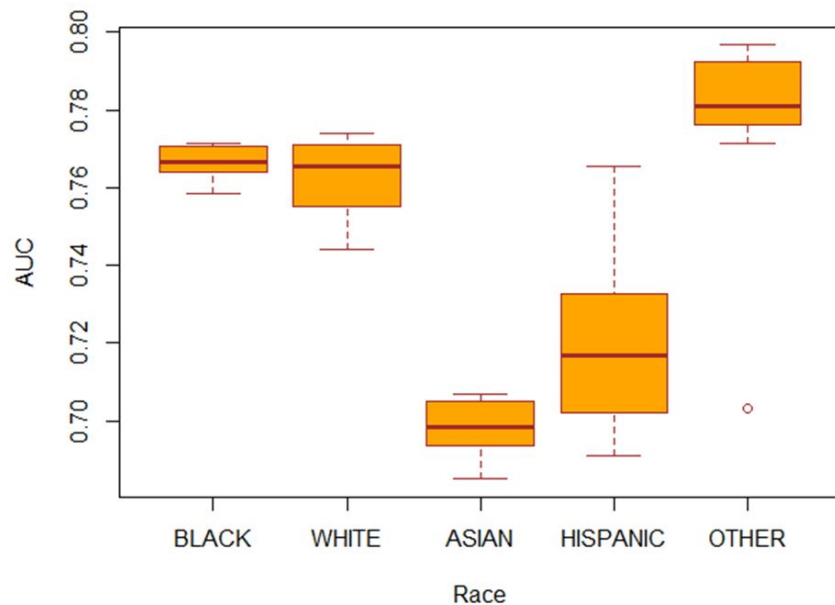
# Exp. 1: CXR→Findings, Subgroup Analysis

## Pneumonia



**AUC for Black > AUC for White**

## Pneumothorax



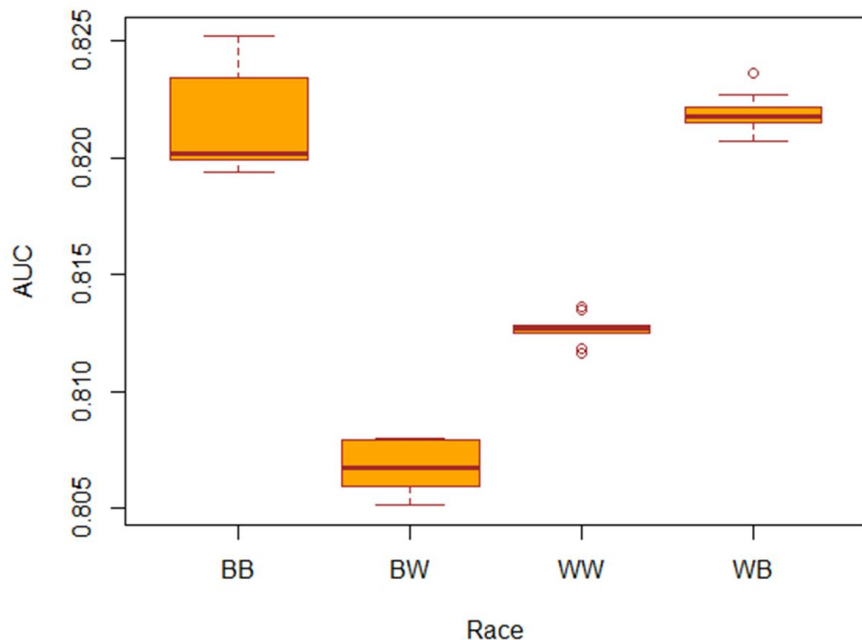
**AUC for Black = AUC for White**

# Experiments

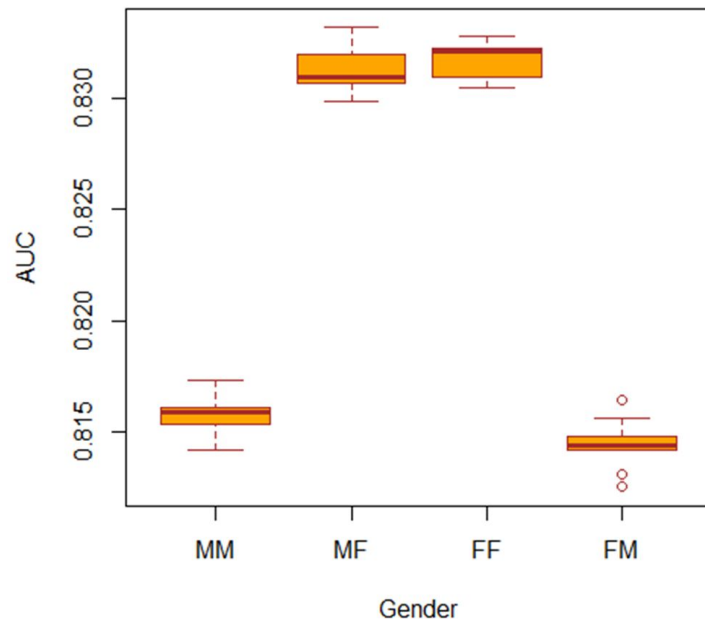
1. CXR embedding predict findings
  - ▶ Standard approach plus **subgroup analysis**
  - ▶ **Performance gap exists ?**
2. CXR embedding predict findings
  - ▶ For gender/race, **train/val on group1, test on group2**
  - ▶ **Need better balancing ?**
3. CXR embedding → group 1 or group 2
  - ▶ Direct **prediction of gender/race**
  - ▶ **Potential spurious correlation ?**

## Exp. 2: CXR→Findings, **Train group1 Test group2**

### Cardiomegaly, Black/White



### Cardiomegaly, Male/Female



**Consistant to PNAS 2020, AUC FF > MF**

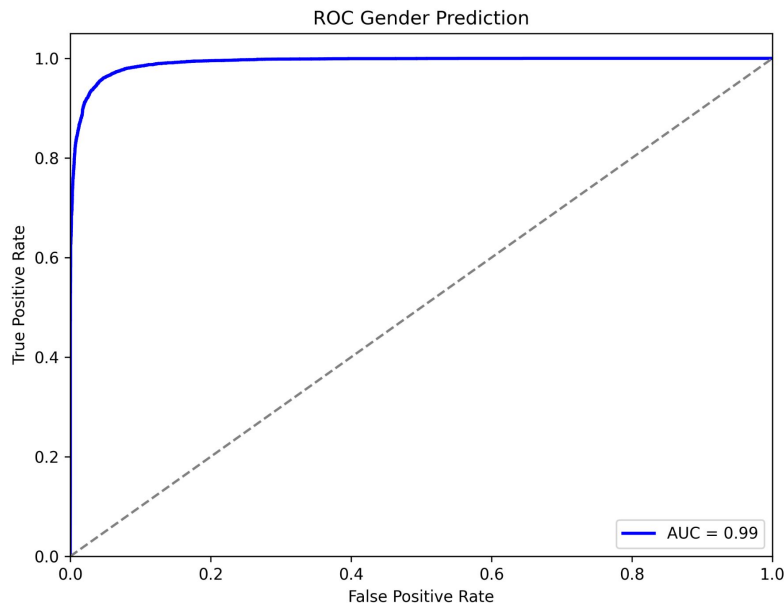
# Experiments

1. CXR embedding predict findings
  - ▶ Standard approach plus **subgroup analysis**
  - ▶ **Performance gap exists ?**
2. CXR embedding predict findings
  - ▶ For gender/race, **train/val on group1, test on group2**
  - ▶ **Need better balancing ?**
3. CXR embedding → **group 1 or group 2**
  - ▶ Direct **prediction of gender/race**
  - ▶ **Potential spurious correlation ?**

# Exp. 3: CXR→Gender/Race

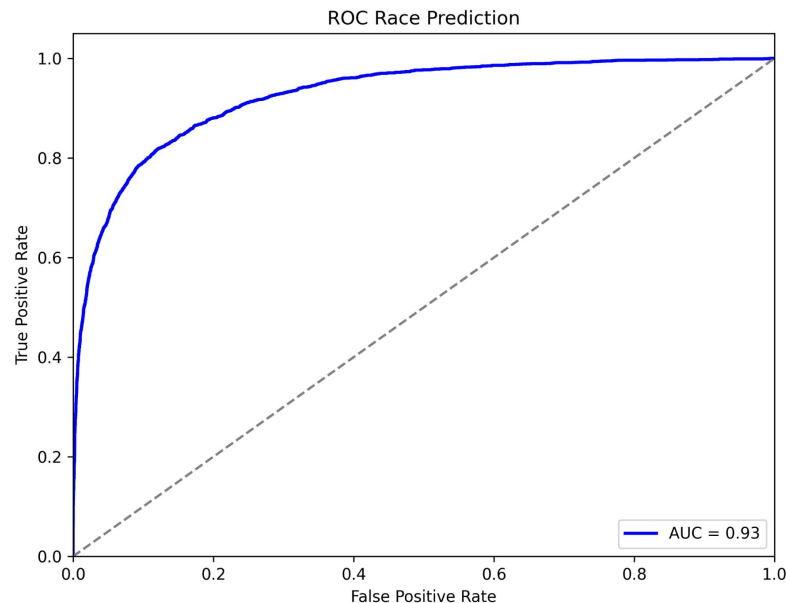
**Predict Gender**

**AUROC = 0.99**



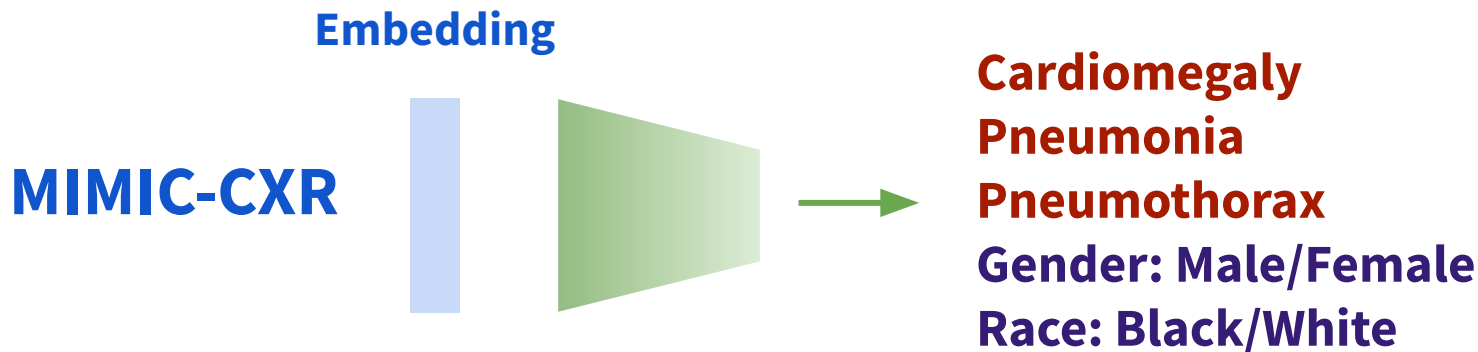
**Predict Race (Black/White)**

**AUROC = 0.93**



**Consistant to Gichoya et al. 2022, AUROC ~0.98**

# Summary - Team 11 -4 The GEMs



- ▷ Embedding + small model
  - ▶ Much faster training and inference
  - ▶ Similar demographic bias results compared to conventional approach
  - ▶ Observed disease-specific bias



## Future Work

- ▷ Head-to-head comparison foundation embedding + MLP vs direct training using DenseNet121/ResNet34
- ▷ Try new/rare findings/diseases e.g. CTD-ILD, LAM
- ▷ Try a collaboration scenario: e.g. MIMIC-CXR + CheXpert predict on Emory CXR or using synthetic data
- ▷ Performance gaps: biased diagnosis or underrepresentation ?
- ▷ Methods to mitigate bias with embedding + MLP: e.g. balancing, adversarial training



Thank You!

Team 11 - 4: The GEMs



# Foundation Model for CXR

👍 or 🗣️ for reducing bias ?

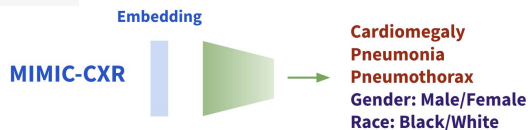
Emory Health Datathon, Team 11 The GEMs



## Clinical Relevance

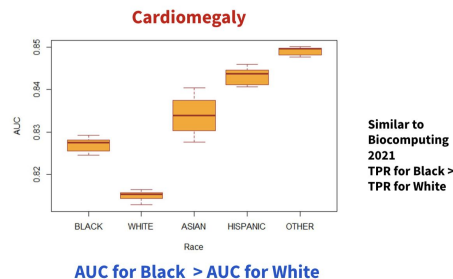
- Embedding + small model
- Much faster training and inference
- Similar demographic bias results compared to
- conventional approach
- Observed disease-specific bias

## Approach

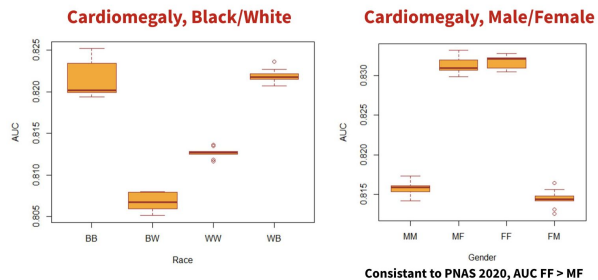


- ▶ Embedding + small model
  - ▶ Much faster training and inference
  - ▶ Similar demographic bias results compared to conventional approach
  - ▶ Observed disease-specific bias

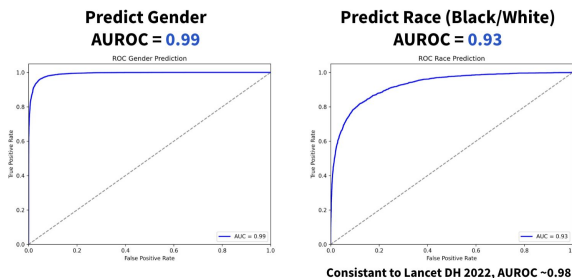
## Exp. 1: CXR→Findings, Subgroup Analysis



## Exp. 2: CXR→Findings, Train group1 Test group2



## Exp. 3: CXR→Gender/Race



## Future Work

- ▶ Head-to-head comparison foundation embedding + MLP vs direct training using DenseNet121/ResNet34
- ▶ Try new/rare findings/diseases e.g. CTD-ILD, LAM
- ▶ Try a collaboration scenario: e.g. MIMIC-CXR + CheXpert predict on Emory CXR or using synthetic data
- ▶ Performance gaps: biased diagnosis or underrepresentation ?
- ▶ Methods to mitigate bias with embedding + MLP: e.g. balancing, adversarial training