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Benchmarking CXR embedding models for disease classification

Jiho Shin, Dominic Marshall, YingYing Fang

The bigger picture: Master Project

- Problem: Acute Respiratory Distress Syndrome (ARDS)
  - Heterogeneous, making diagnosis, prognosis and personalised treatment challenging
- Solution: Machine Learning – Deep Representation Learning for Clinical Clustering (ML-DRLCC)
  - A multimodal deep learning framework aimed at identifying clinically meaningful subtypes in ARDS

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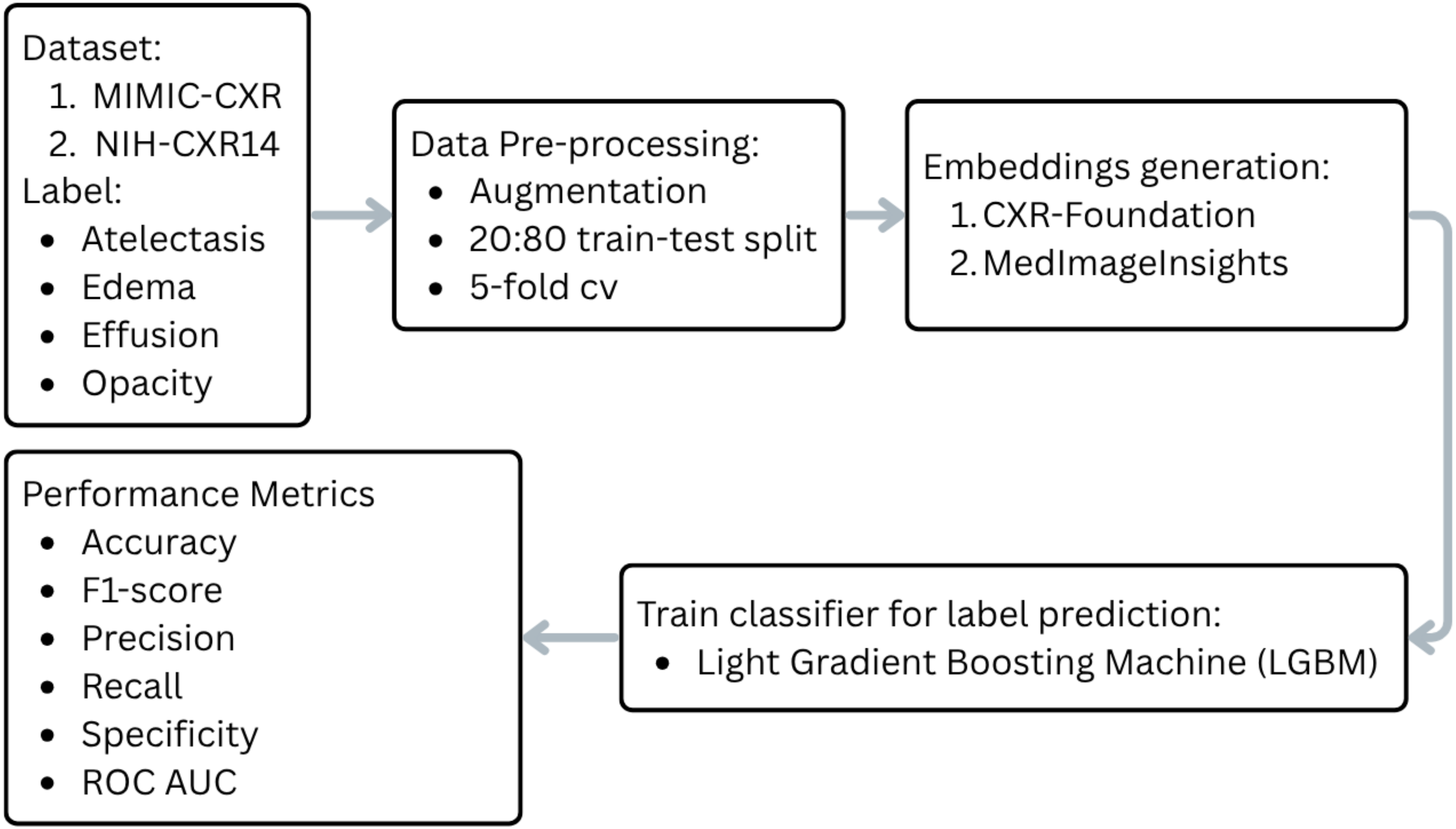
Motivation

- Benchmarking CXR embedding models to select the optimal CXR image representation for integration into ML-DRLCC
- Potential of CXR embedding models for patient representation

Workflow


Dataset:
1. MIMIC-CXR
2. NIH-CXR14
Label:
• Atelectasis
• Edema
• Effusion
• Opacity
Data Pre-processing:
• Augmentation
• 20:80 train-test split
• 5-fold cv
Embeddings generation:
1. CXR-Foundation
2. MedImageInsights
Train classifier for label prediction:
• Light Gradient Boosting Machine (LGBM)
Performance Metrics
• Accuracy
• F1-score
• Precision
• Recall
• Specificity
• ROC AUC

Dataset

Open-source datasets:

1. MIMIC CXR
2. NIH-CXR14

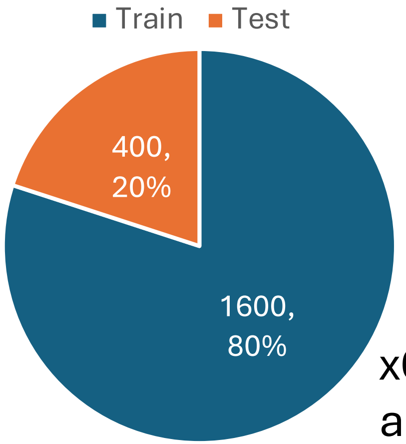
Disease labels

1. Opacity
2. Atelectasis
3. Edema
4. Effusion

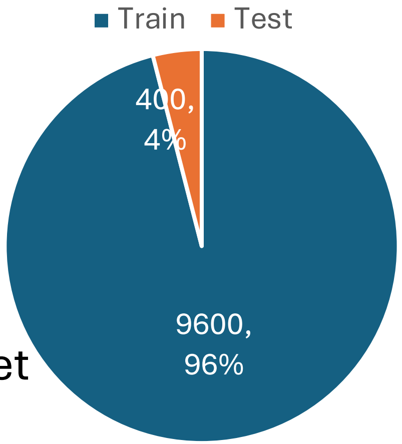
For each disease label and dataset (MIMIC, NIH):

- 0: Absence of disease label → 1000 images
- 1: Presence of disease label → 1000 images

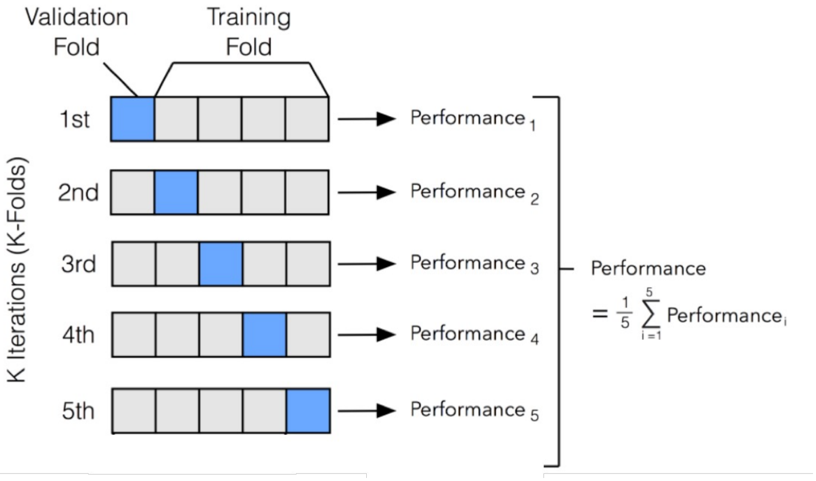
Data preprocessing and train-test split



x6 train dataset augmentation



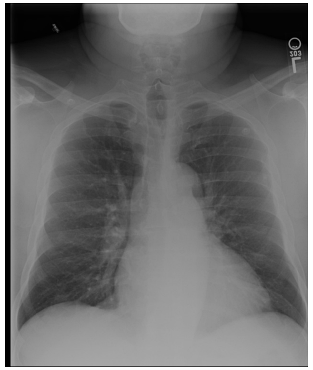
- <u>K=5 fold cross-validation:</u>



- Augmentation

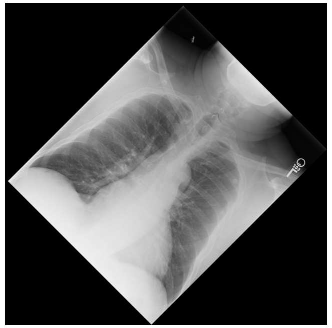
Original

Bright



Dark

Contrast



Rot +45 deg

Rot -45 deg

Model 1: CXR-Foundation (2023)

Overview & Features

- **ELIXR v2.0**: rich 32×768-dimensional vectors.

Benchmark Results

- Delivers **high AUC (89% for tube placement assessment)** on classification tasks and strong retrieval performance

Limitations

- Trained on US/India data only; may not generalise globally.
- Large data dimension (32x768)

arXiv > cs > arXiv:2308.01317

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[Submitted on 2 Aug 2023 (v1), last revised 7 Sep 2023 (this version, v2)]

ELIXR: Towards a general purpose X-ray artificial intelligence system through alignment of large language models and radiology vision encoders

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Model 2: MedimageInsight (2024)

Overview & Features

- Embeddings: **1,024 vectors** used for similarity indexing

Benchmark Results

- On a radiographic tube-placement classification dataset (8,842 images), embeddings achieved **mean AUC of 93.8 %**, vs. **89 % (CXR-Foundation)**

Strengths

- Bone-age estimation and other tasks achieved AUC > 0.9.
- Efficient and adaptable to lightweight classifiers.
- Compact representation (1024 [MedImageInsight] vs 32x768 [CXR-foundation])

arXiv > eess > arXiv:2410.06542

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Electrical Engineering and Systems Science > Image and Video Processing

[Submitted on 9 Oct 2024]

MedImageInsight: An Open-Source Embedding Model for General Domain Medical Imaging

Results: Accuracy (95% CI: $\pm\ error$)

		MedImageInsights	CXR-foundation
MIMIC	Atelectasis	**0.75 ± 0.0073**	**0.75 ± 0.0075**
	Edema	0.84 ± 0.014	**0.85 ± 0.024**
	Effusion	**0.90 ± 0.026**	0.88 ± 0.0098
	Opacity	**0.70 ± 0.016**	0.70 ± 0.023
Average		0.80 ± 0.0087	0.80 ± 0.0088
NIH-14	Atelectasis	**0.78 ± 0.016**	0.75 ± 0.023
	Edema	**0.85 ± 0.019**	0.83 ± 0.013
	Effusion	0.83 ± 0.014	0.83 ± 0.0080
	Opacity	0.85 ± 0.019	**0.89 ± 0.013**
Average		**0.83 ± 0.0087**	0.82 ± 0.0076

Results: AUROC (95% CI: $\pm\ error$)

		MedImageInsights	CXR-foundation
MIMIC	Atelectasis	**0.83 ± 0.0069**	0.82 ± 0.013
	Edema	0.92 ± 0.011	0.92 ± 0.014
	Effusion	**0.96 ± 0.012**	0.94 ± 0.0060
	Opacity	**0.78 ± 0.019**	0.77 ± 0.017
Average		**0.87 ± 0.0065**	0.86 ± 0.0066
NIH-14	Atelectasis	**0.86 ± 0.0079**	0.82 ± 0.012
	Edema	**0.92 ± 0.012**	0.91 ± 0.015
	Effusion	0.90 ± 0.011	0.90 ± 0.011
	Opacity	0.92 ± 0.012	**0.96 ± 0.010**
Average		0.90 ± 0.0054	0.90 ± 0.0061

Results

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- Two models exhibit almost identical performance while MedImageInsight model slightly outperforms CXR foundation in general
- Similar performance metrics across disease labels (within ± 0.04 difference), while they differ significantly across different disease labels

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Discussion

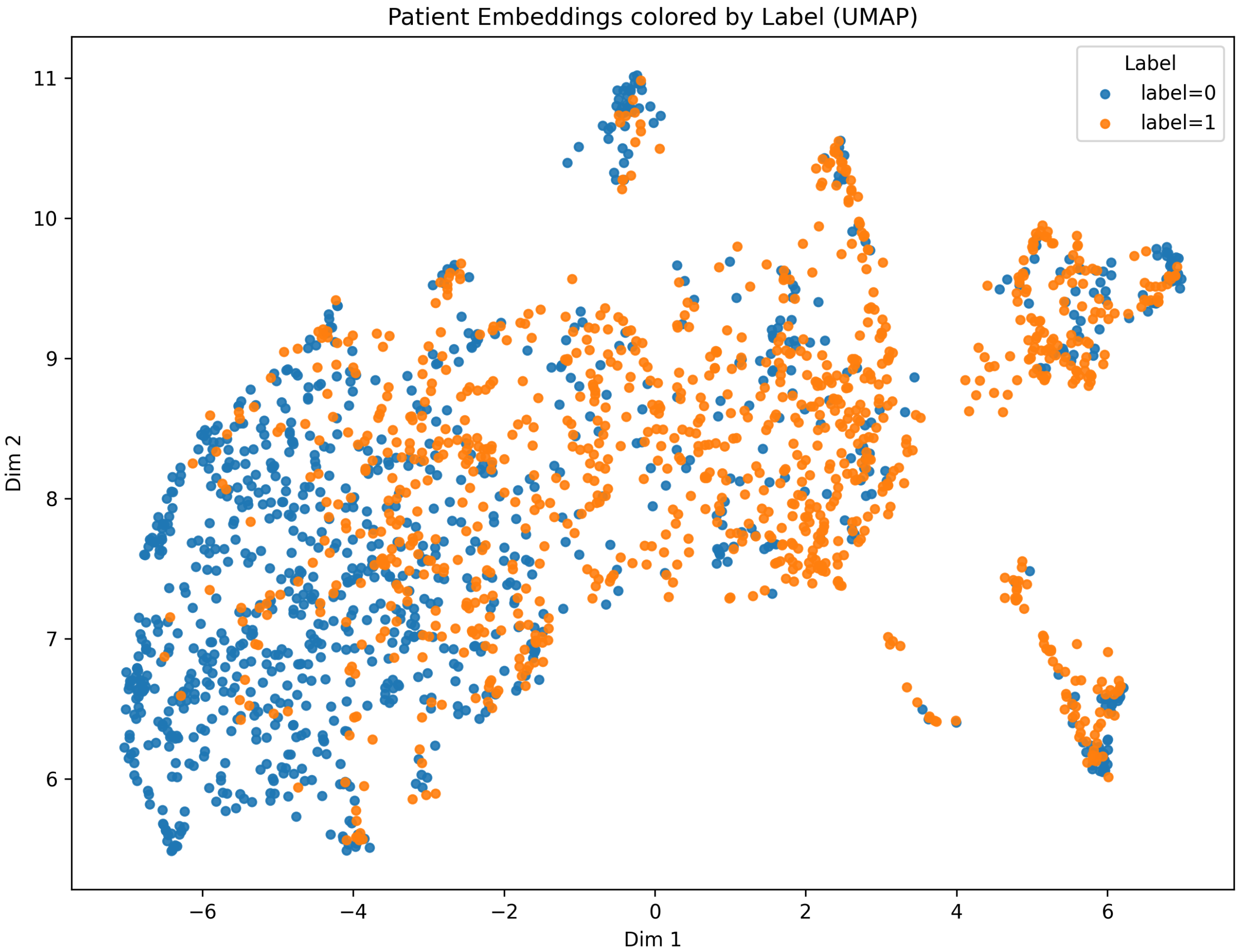
- The MedImageInsight model might be the ideal option as it has a smaller embedding dimension (1024) compared to the CXR Foundation (32x768), with similar performance.
  - Low computational cost
  - Theoretically, more advantageous for clustering (lower noise level)
  - Lower risk of overfitting
- Model architecture and feature extraction method may not be the limiting factor — the nature of the disease label itself may drive performance differences.

Clustering: MedImageInsight & MIMIC

1. **K-Nearest Neighbour (KNN)** from CXR embeddings (cosine similarity, k=15).
2. Applied **Leiden community detection** to find patient subgroups in the embedding space.
3. Dimensionality reduced with **UMAP** for visualization

Clustering

MedImageInsights/MIMIC/Atelectasis



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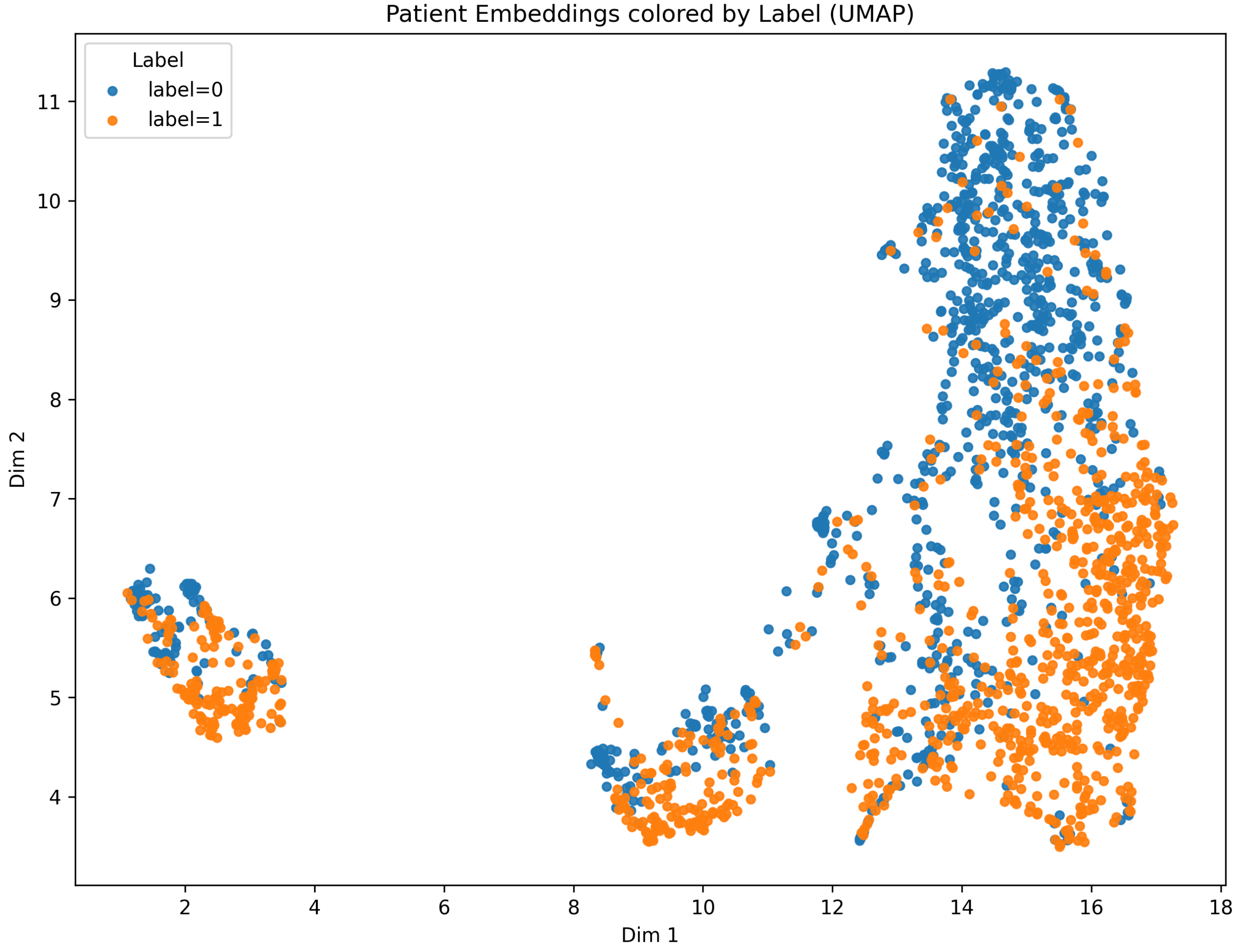
Clustering

MedImageInsights/MIMIC/Edema



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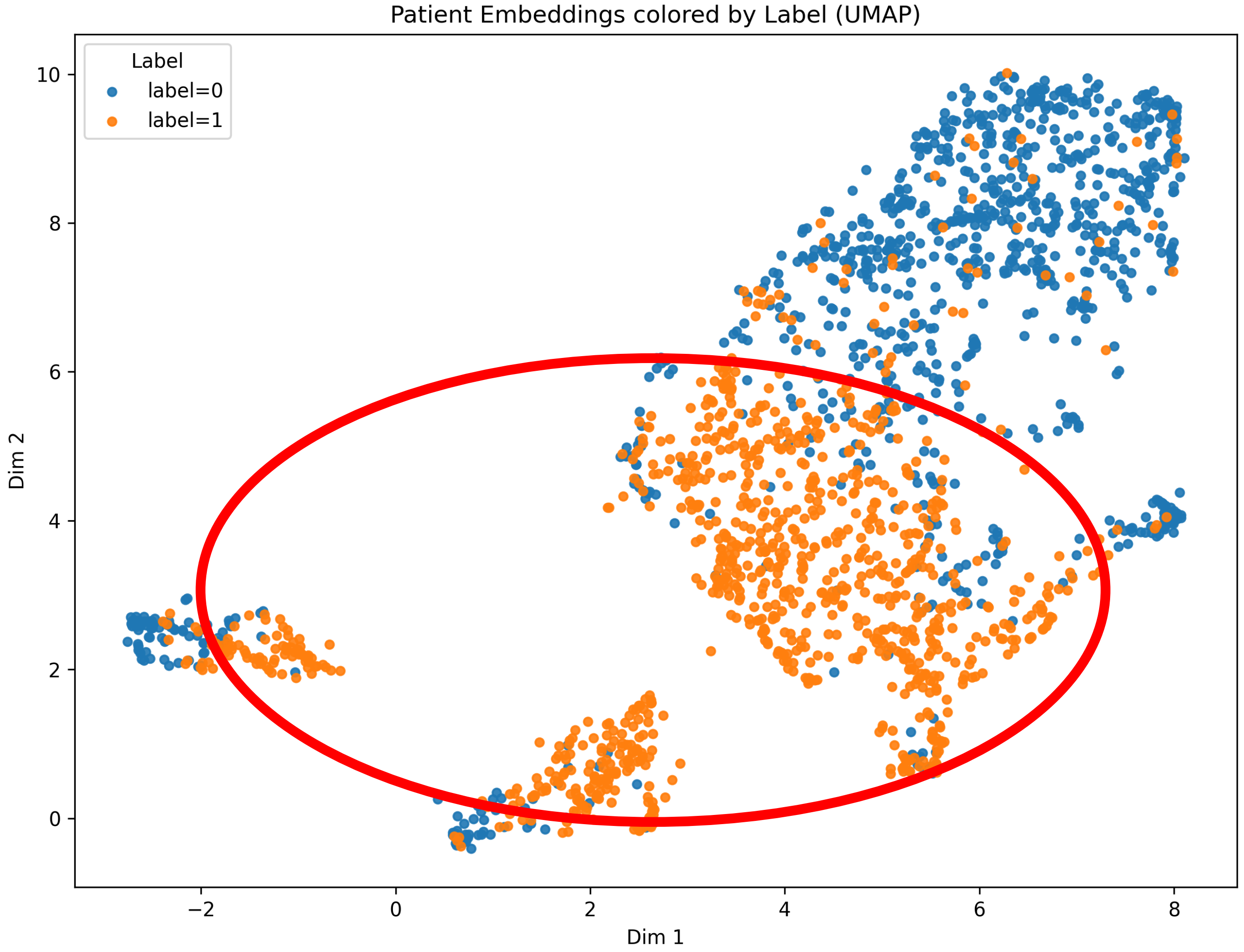
Clustering

MedImageInsights/MIMIC/Effusion



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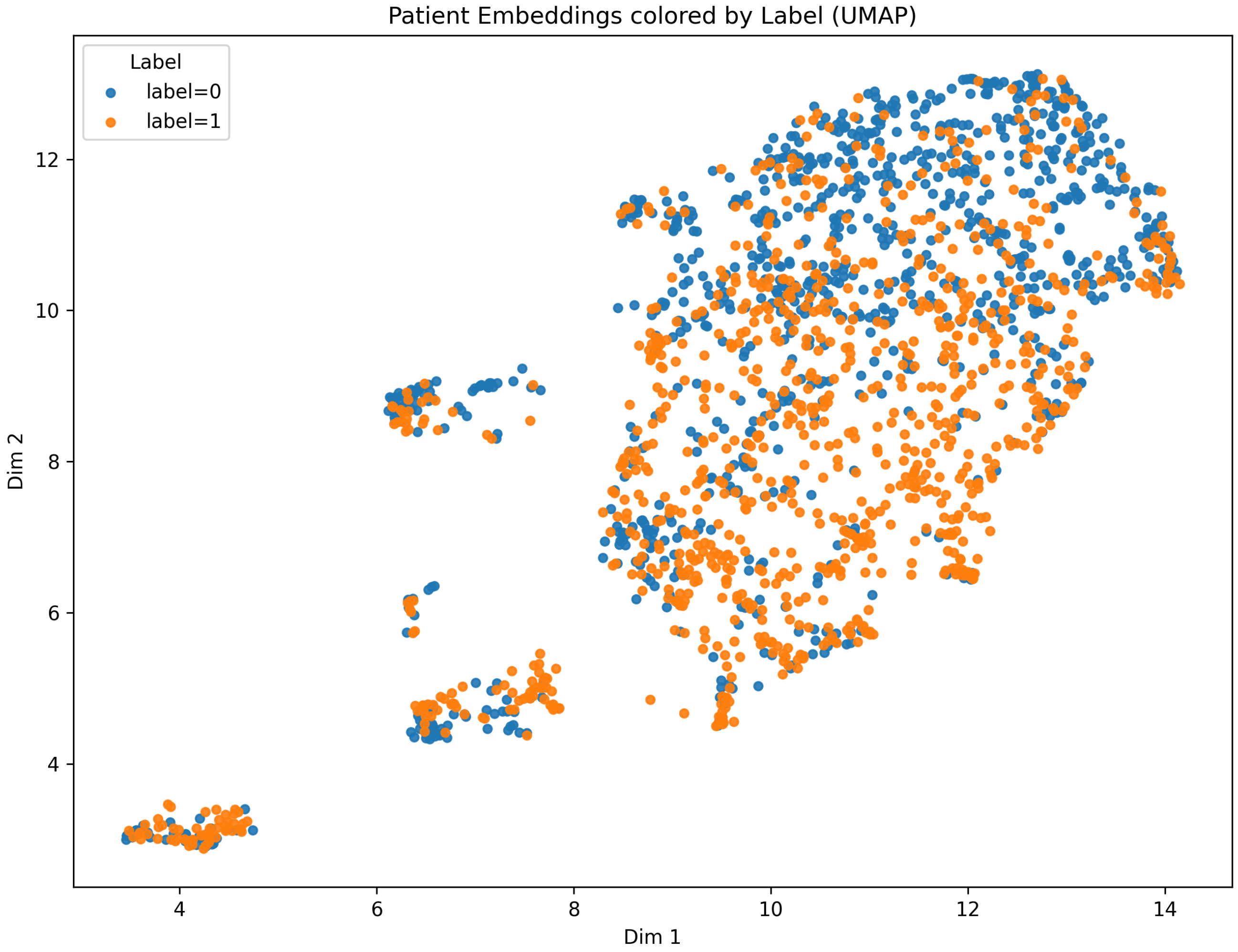
Clustering

MedImageInsights/MIMIC/Opacity



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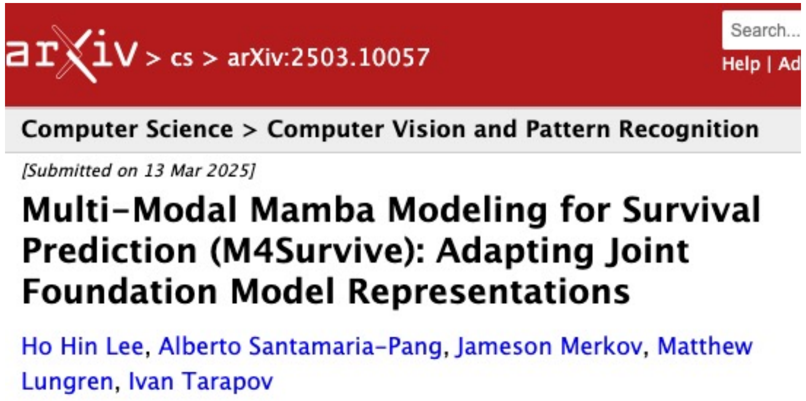
Model architecture and feature extraction method may not be the limiting factor

- Integration with clinical data?
- Improve training dataset quality (e.g. Better augmentation)?

Future Steps

- Use cxr embedding model to fuse with clinical data to find meaningful patient clusters for Acute Respiratory Distress Syndrome (ARDS)
- Investigate how to combine clinical data with cxr embeddings
  - Variational Auto encoders (VAEs)
  - M4survive


arXiv > cs > arXiv:2503.10057

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[Submitted on 13 Mar 2025]

Multi-Modal Mamba Modeling for Survival Prediction (M4Survive): Adapting Joint Foundation Model Representations

Ho Hin Lee, Alberto Santamaria-Pang, Jameson Merkov, Matthew Lungren, Ivan Tarapov