MedFusion
ANALYTICS

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Cinthya Rosales, Adam Saleh,
Esteban Valenzuela

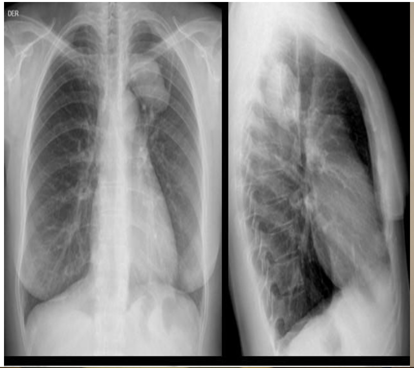
DATASCI 210, Section 6

Current Diagnostic Models Utilize Only One Data Type

- **Inadequate Utilization** of EHR Data Systems

- Barriers to **Accessing Complex Insights** For Physicians

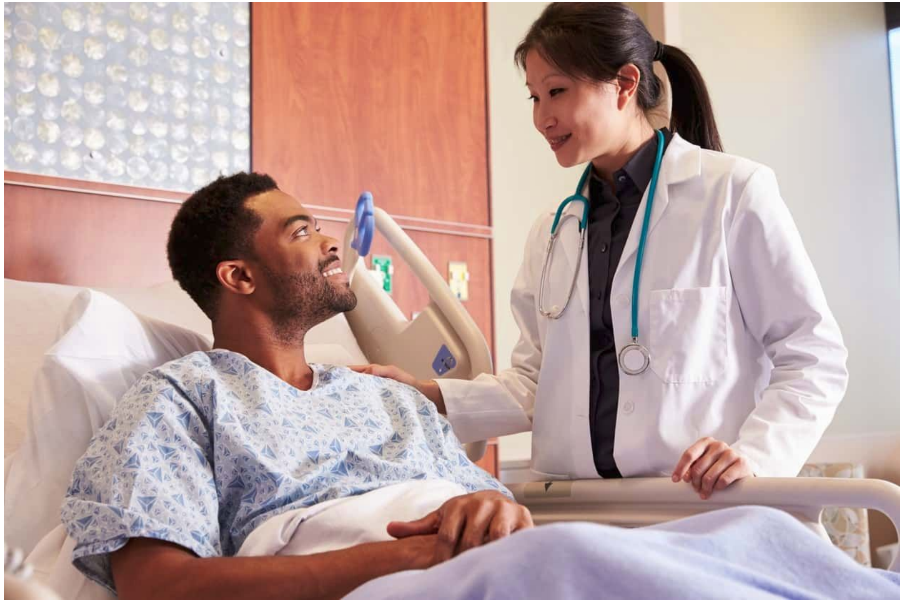
- Limitations in AI for **Comprehensive Diagnostics**



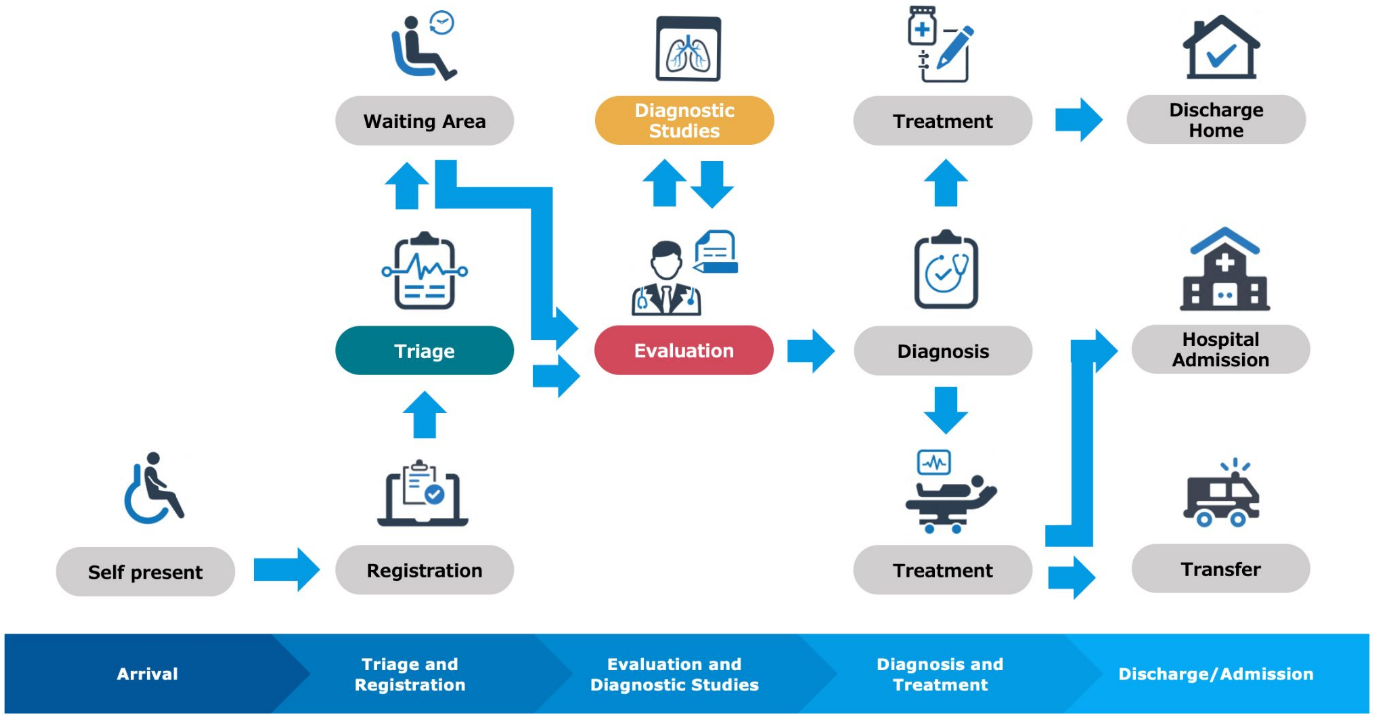
Introducing MedFusion Analytics - The Future of Diagnostic Precision

A pioneering multi-modal model to predict top pathological findings in chest X-rays

- **Combines** patient data, clinician notes, and radiology images
- **Tailored** for healthcare researchers and attending physicians
- **Empowers** users to harness AI-based diagnostic insights
- **Easy-to-use** tool allows for seamless integration

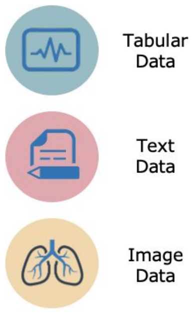


Data: MIMIC-IV

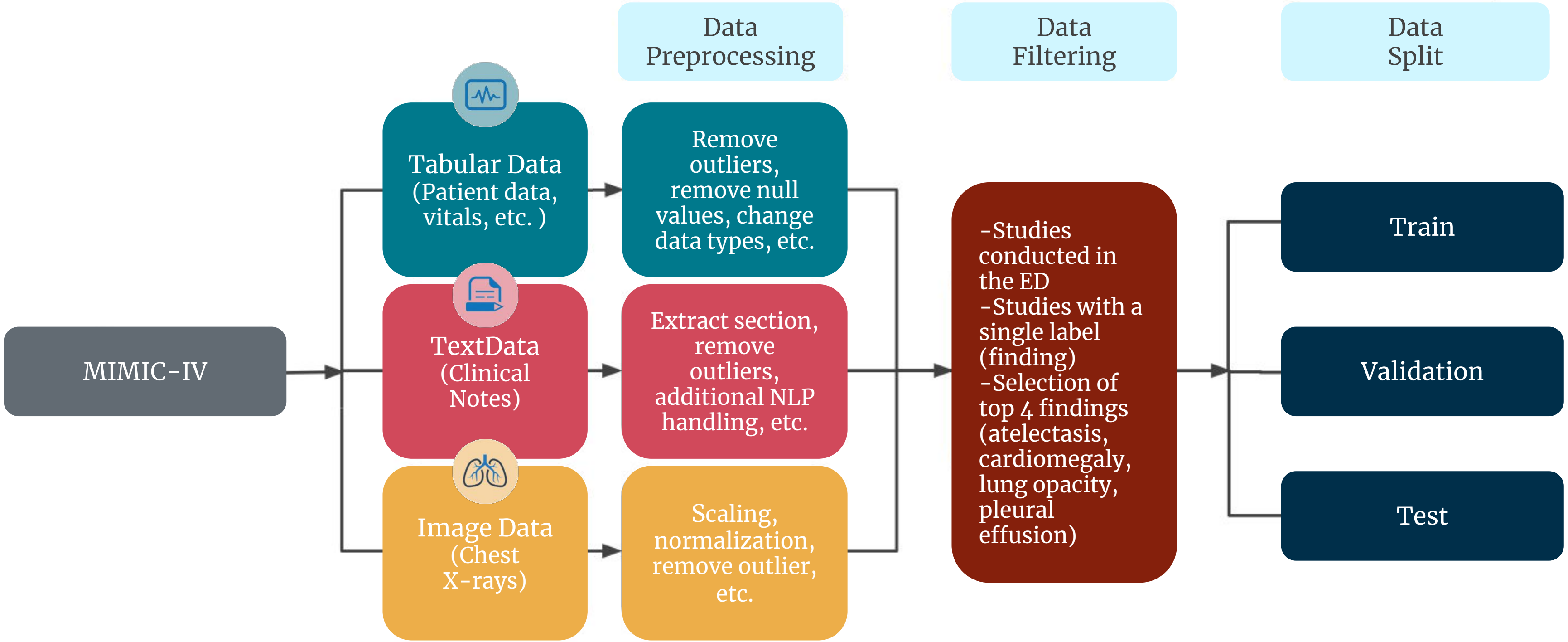


MIMIC-IV

Medical Information Mart for Intensive Care



Data Processing Pipeline

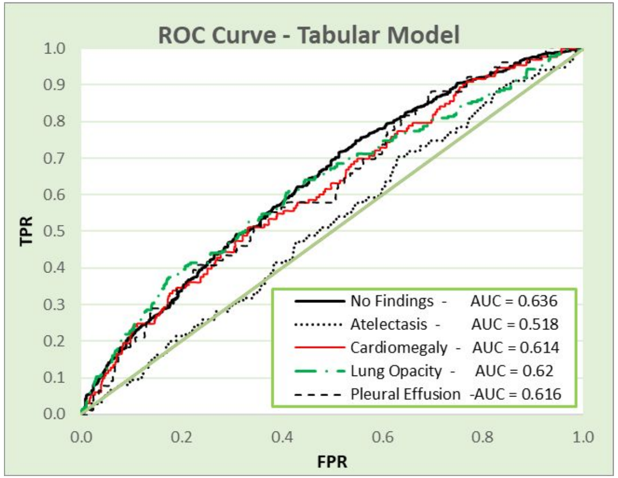


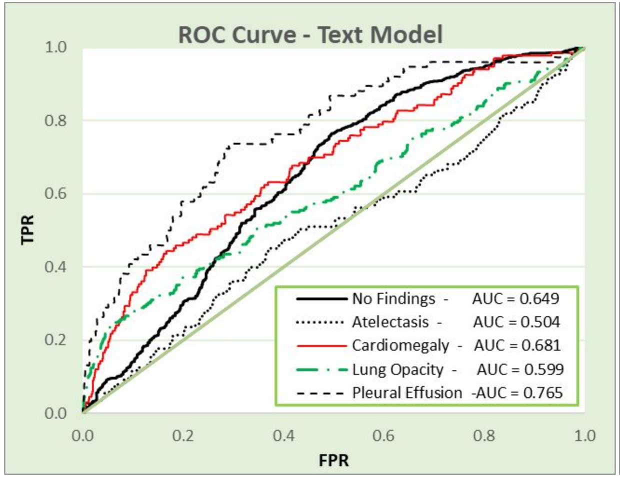
Individual Model Performance

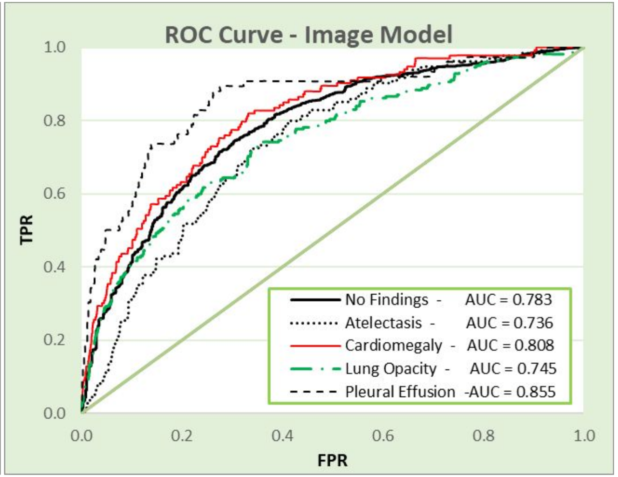
Tabular Model
(XGBoost)

Text Model
(Bio_ClinicalBERT)

Image Model
(EfficientNet-B3)







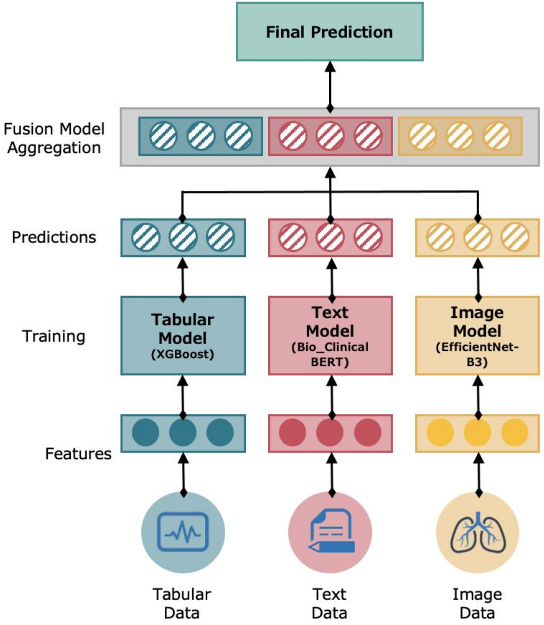
Revolutionizing Diagnostics with Multi-Model Integration

Late Fusion

Most multi-modal models today

Good at dealing with missing data

Aggregation functions need to be empirically determined

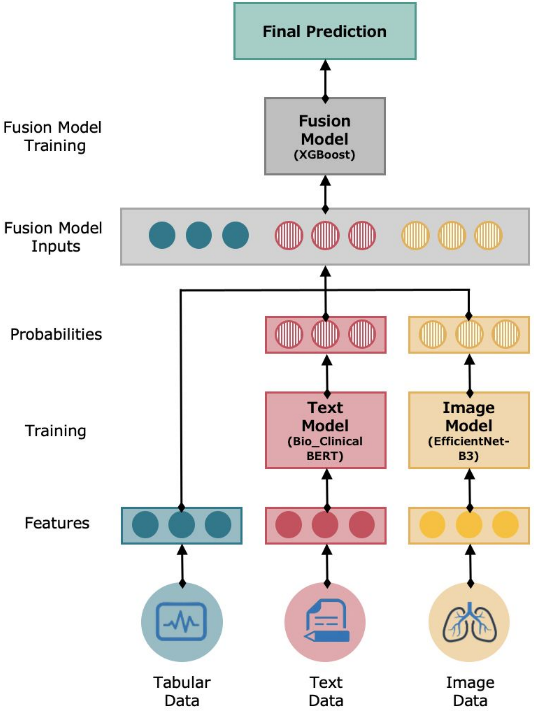


Early Fusion

A final model determines the final prediction

Able to model interactions between modalities

Potential for better performance



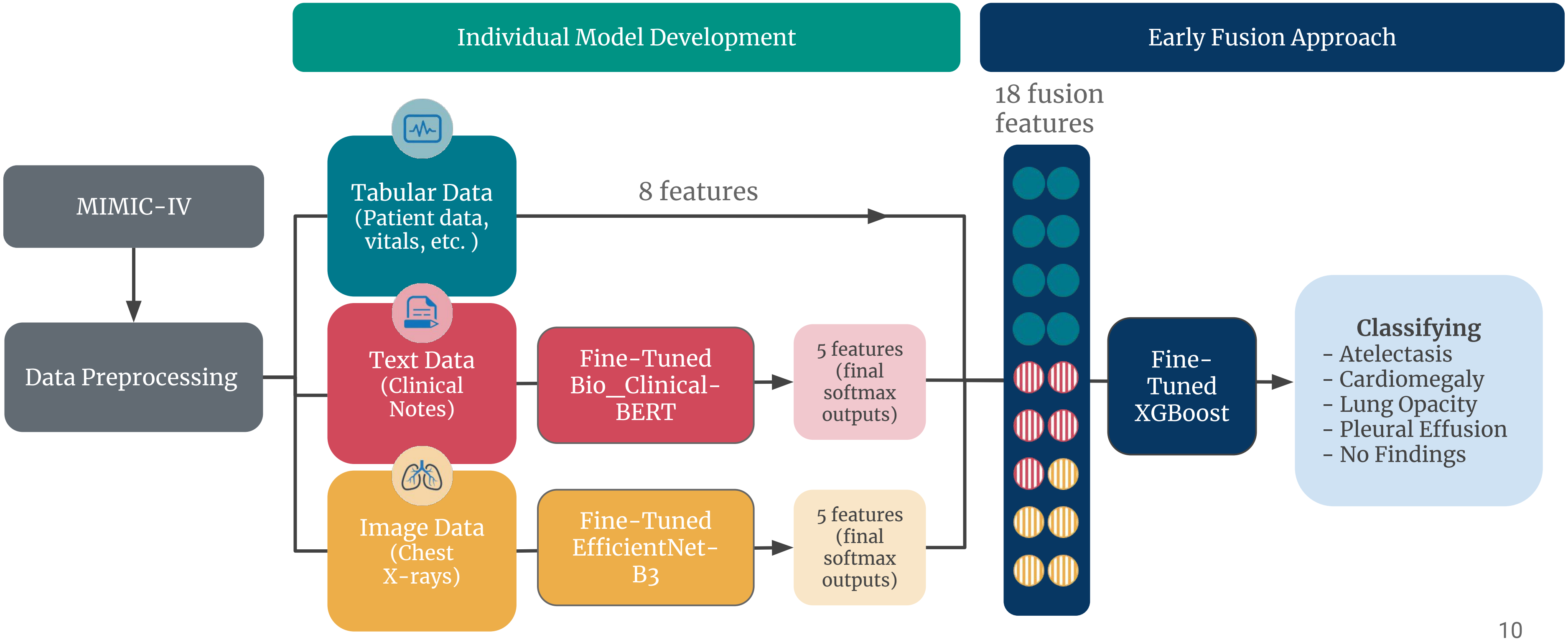
MedFusion Analytics Web Demo

https://uc-berkeley-i-school.github.io/mids-210-medfusion-analytics-spring24/

Tabular Inference

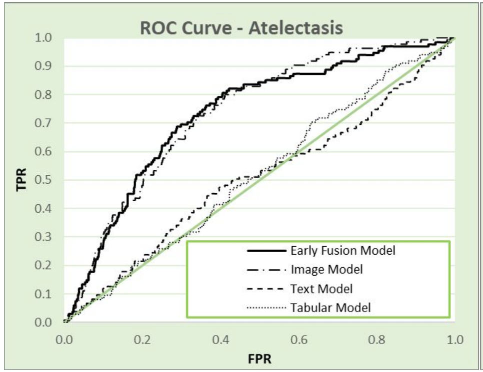
Results:

Early Fusion Model Pipeline – From Data to Diagnosis



Early Fusion Outperforms Individual Models

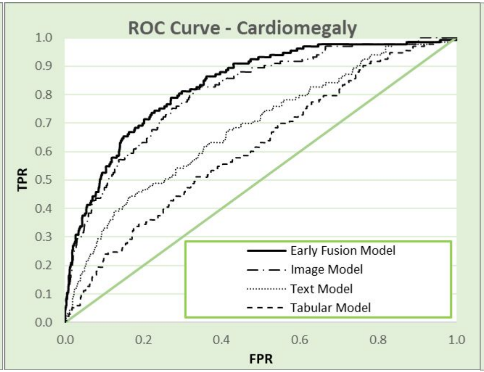
Atelectasis



AUC

Early Fusion: 0.7319
Image: 0.7361
Notes: 0.5042
Tabular: 0.5184

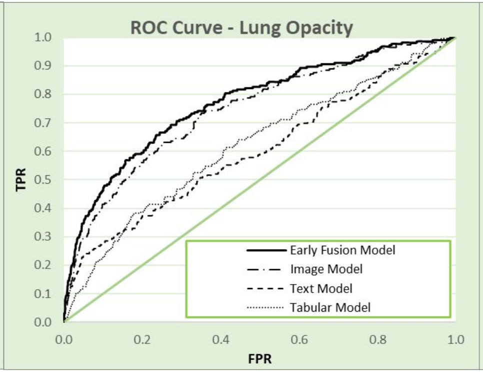
Cardiomegaly



AUC

Early Fusion: 0.8350
Image: 0.8080
Notes: 0.6811
Tabular: 0.6140

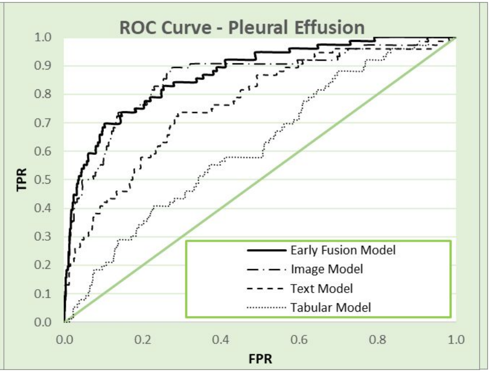
Lung Opacity



AUC

Early Fusion: 0.7713
Image: 0.7450
Notes: 0.5994
Tabular: 0.6204

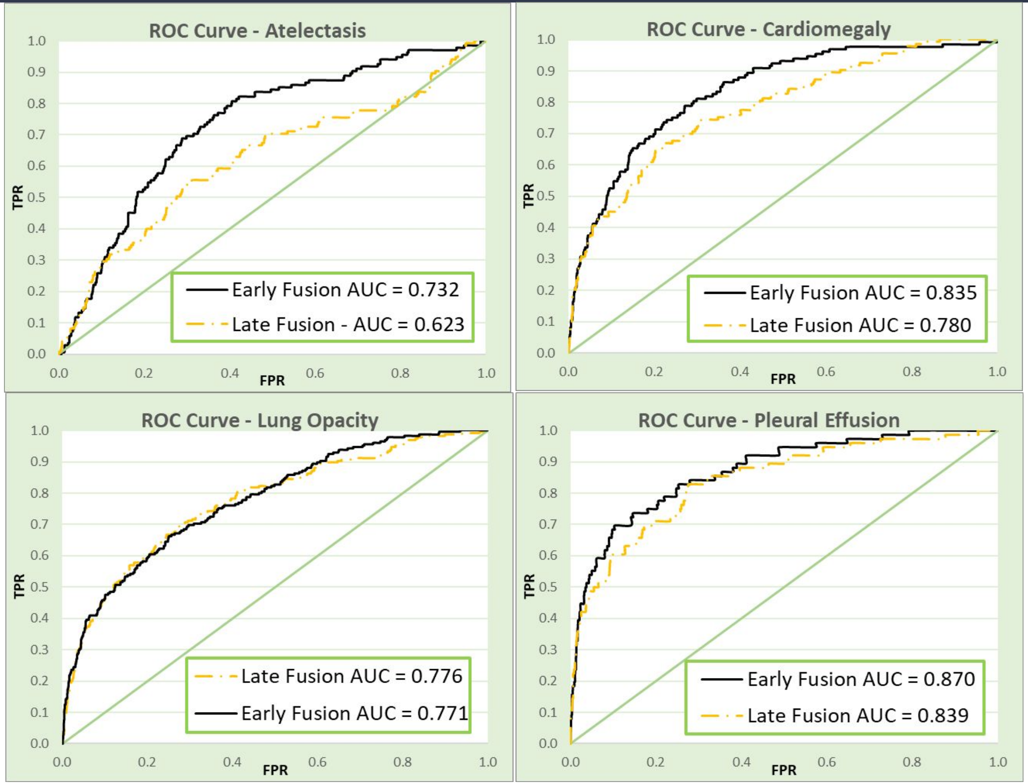
Pleural Effusion



AUC

Early Fusion: 0.8705
Image: 0.8548
Notes: 0.7654
Tabular: 0.6164

Redefining Standards with Early Fusion



Compared to an average late fusion aggregator, our early fusion model has:

- Superior AUC
- Sharper Detection
- Robust Across Pathologies
- Sets New Norms

MedFusion Analytics: Transforming Healthcare Diagnostics

Early Fusion Approach: Our pioneering multi-modal model integrates patient data, clinician notes, and radiology images for accurate diagnosis.

Key Benefits:

- **Real-time predictions in seconds**
- **Intuitive user interface**
- **Comprehensive documentation to promote model transparency**

MedFusion
ANALYTICS

Our Mission: Revolutionize patient care by harnessing the power of multi-modal data

Our Mission Pillars

Pioneering Novelty

Precision & Personalization

Empowering Physicians

Enhancing Patient Outcomes

Shaping the Future of Healthcare

References

1. Huang, SC., Pareek, A., Seyyedi, S. *et al.* Fusion of medical imaging and electronic health records using deep learning: a systematic review and implementation guidelines. *npj Digit. Med.* 3, 136 (2020). https://doi.org/10.1038/s41746-020-00341-z
2. Soenksen, L.R., Ma, Y., Zeng, C. *et al.* Integrated multimodal artificial intelligence framework for healthcare applications. *npj Digit. Med.* 5, 149 (2022). https://doi.org/10.1038/s41746-022-00689-4
3. Kline, A., Wang, H., Li, Y. *et al.* Multimodal machine learning in precision health: A scoping review. *npj Digit. Med.* 5, 171 (2022). https://doi.org/10.1038/s41746-022-00712-8

Appendix

Insights from the Frontlines

"[current clinical decision support systems] increased the workload ... more steps, discrete ... instead of writing a **free-text** reason for your study"

MARC KOHLI, M.D.
Radiologist, Professor of Radiology, UCSF

"...we need a decision support tool to provide an opportunity to **cut down on time** required for physicians to make a **diagnosis...** as a consequence we **improve the patient experience**..."

JOSEPH NGUYEN, M.D.
Radiologist, Synergy Radiology Associates

"...our problem is **resources...** radiologists may take **2 to 6 hours** to return a reading..."

MOHIT BANSAL, M.D.
Family Physician, Lifeline Urgent Care

"Image analysis is very hot in radiology right now ... [it takes] long time until you **incorporate** the rest of the things in the chart..."

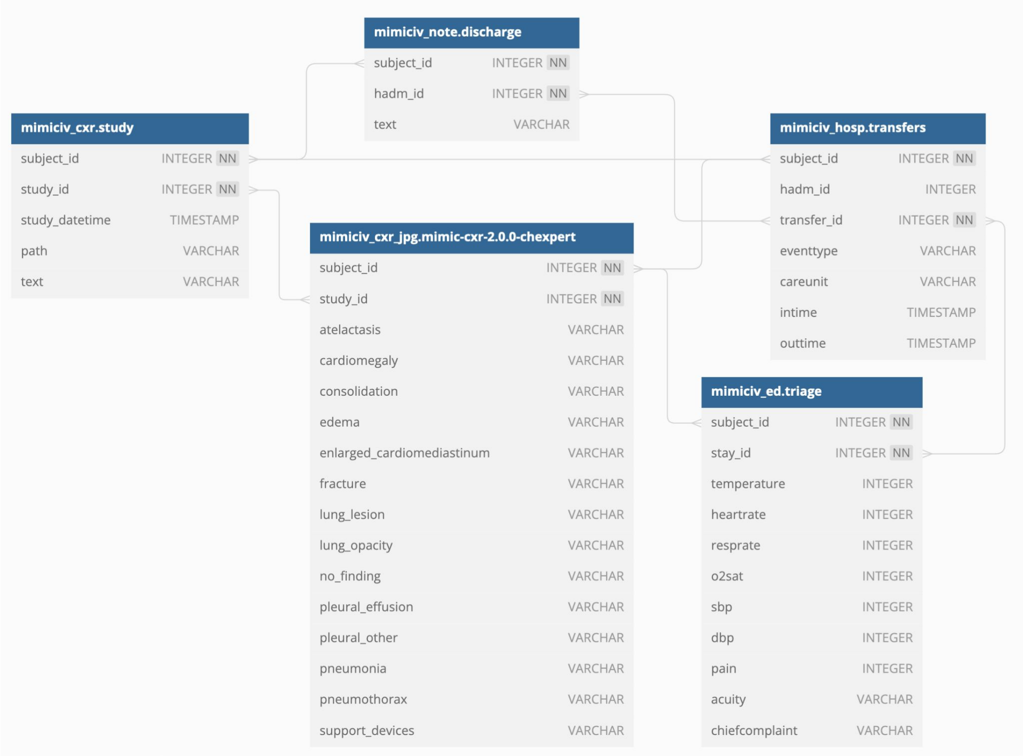
RONALD CRANDALL, M.D.
Radiology Resident, Richmond University Medical Center

EDA: Combining Notes, CXR (Images) with other MIMIC Modules

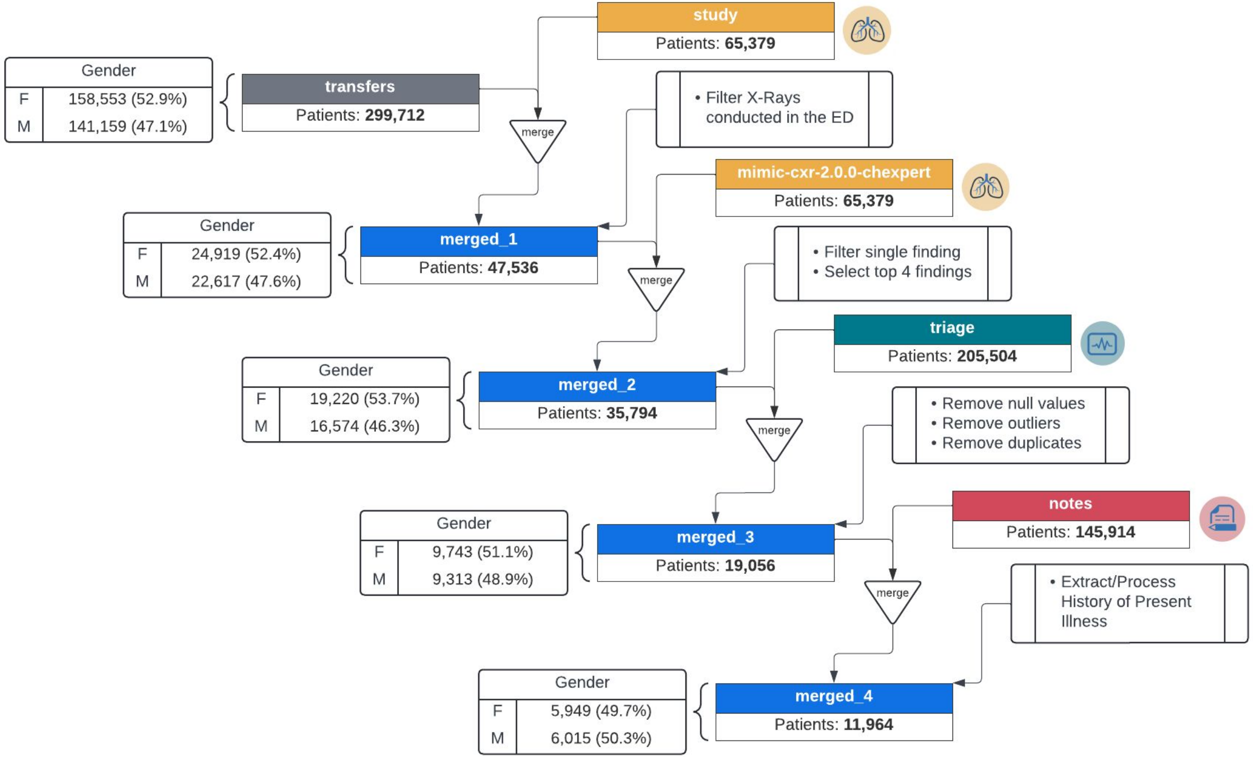
People w/ Discharge Notes & Images By Module

source	total_count	notes_overlap	notes_proportion_of	cxr_overlap	cxr_proportion_of_ta	both_overlap	both_proportion_of_table
MIMICIV_Derived_Age	180733	145914	0.807345642467...	51299	0.283838590628...	45935	0.2541594506813919
MIMICIV_ECG	161352	111647	0.691946799543...	54362	0.336915563488...	42511	0.263467450047102
MIMICIV_ED_Edstays	205504	100470	0.488895593273...	61856	0.300996574275...	45922	0.22346037060105886
MIMICIV_Hosp_Admissions	180733	145914	0.807345642467...	51299	0.283838590628...	45935	0.2541594506813919
MIMICIV_ICU_Icustays	50920	50496	0.991673212882...	19264	0.378318931657...	19227	0.37759230164964652
MIMICIV_Note_Discharge	145914	145914	1.0	45935	0.314808722946...	45935	0.31480872294639306
MIMIC_CXR	65379	45935	0.702595634683...	65379	1.0	45935	0.70259563468392

Data Processing – MIMIC-IV Modules



Data Processing – Pipeline



Data Processing - Split

Train Dataset					
train_set__chexpert__4_findings__single_label__unbalanced.json					
	finding	not_mention	positive_mention	total_studies	percentage
0	no_finding	2,228	5,530	7,758	71.3%
1	lung_opacity	6,865	893	7,758	11.5%
2	cardiomegaly	7,242	516	7,758	6.7%
3	atelectasis	7,292	466	7,758	6.0%
4	pleural_effusion	7,405	353	7,758	4.6%

Validation Dataset					
validation_set__chexpert__4_findings__single_label__unbalanced.json					
	finding	not_mention	positive_mention	total_studies	percentage
0	no_finding	557	1,382	1,939	71.3%
1	lung_opacity	1,716	223	1,939	11.5%
2	cardiomegaly	1,810	129	1,939	6.7%
3	atelectasis	1,822	117	1,939	6.0%
4	pleural_effusion	1,851	88	1,939	4.5%

Test Dataset					
test_set__chexpert__4_findings__single_label__unbalanced.json					
	finding	not_mention	positive_mention	total_studies	percentage
0	no_finding	557	1,381	1,938	71.3%
1	lung_opacity	1,715	223	1,938	11.5%
2	cardiomegaly	1,809	129	1,938	6.7%
3	atelectasis	1,822	116	1,938	6.0%
4	pleural_effusion	1,849	89	1,938	4.6%

Train Dataset - Balanced					
train_set__chexpert__4_findings__single_label__balanced.json					
	finding	not_mention	positive_mention	total_studies	percentage
0	no_finding	1,412	706	2,118	33.3%
1	atelectasis	1,765	353	2,118	16.7%
2	cardiomegaly	1,765	353	2,118	16.7%
3	lung_opacity	1,765	353	2,118	16.7%
4	pleural_effusion	1,765	353	2,118	16.7%

Train Dataset - Balanced					
train_set__chexpert__4_findings__single_label__balanced.json					
	finding	not_mention	positive_mention	total_studies	percentage
0	no_finding	1,412	353	1,765	20.0%
1	atelectasis	1,412	353	1,765	20.0%
2	cardiomegaly	1,412	353	1,765	20.0%
3	lung_opacity	1,412	353	1,765	20.0%
4	pleural_effusion	1,412	353	1,765	20.0%

Data Processing – Pathology Selection

pathologies	sum	percentage	cumsum_percentage
no_finding	65,282	30.1%	30.1%
no_finding, support_devices	10,173	4.7%	34.8%
lung_opacity	9,605	4.4%	39.2%
cardiomegaly	7,358	3.4%	42.6%
atelectasis	5,253	2.4%	45.0%
...	...	...	...
cardiomegaly, edema, enlarged_cardiomediastinum, lung_lesion, pleural_effusion, support_devices	1	0.0%	100.0%
cardiomegaly, edema, enlarged_cardiomediastinum, lung_opacity, pneumothorax, support_devices	1	0.0%	100.0%
atelectasis, cardiomegaly, consolidation, edema, lung_lesion, pleural_effusion, support_devices	1	0.0%	100.0%
cardiomegaly, edema, enlarged_cardiomediastinum, pleural_effusion, pneumonia, support_devices	1	0.0%	100.0%
cardiomegaly, edema, enlarged_cardiomediastinum, lung_opacity, pleural_other, support_devices	1	0.0%	100.0%

1726 rows × 3 columns

Multiple combinations (multilabel)

Look for the top 4 findings/pathologies

	pathology	not_mention	positive_mention
0	no_finding	152372	75455
1	support_devices	157783	66558
2	pleural_effusion	146369	54300
3	lung_opacity	173233	51525
4	atelectasis	180488	45808
5	cardiomegaly	167071	44845
6	edema	175168	27018
7	pneumonia	186933	16556
8	consolidation	209082	10778
9	pneumothorax	175113	10358
10	enlarged_cardiomediastinum	215365	7179
11	lung_lesion	220681	6284
12	fracture	222551	4390
13	pleural_other	225690	2011

Positive mentions for the top 4 findings/pathologies after cleaning the data
(they total 64 combinations)

	pathology	not_mention	positive_mention	total_studies	percent
0	no_finding	7674	9300	16974	54.79
1	lung_opacity	13644	3330	16974	19.62
2	atelectasis	14748	2226	16974	13.11
3	pleural_effusion	14879	2095	16974	12.34
4	cardiomegaly	15224	1750	16974	10.31

Data Processing – Notes

Name: ___ Unit No: ___

Admission Date: ___ Discharge Date: ___

Date of Birth: ___ Sex: F

Service: MEDICINE

Allergies:
Sulfa (Sulfonamide Antibiotics) / Codeine / Bactrim

Attending: ___.

Chief Complaint:
Weakness, nausea/vomiting

Major Surgical or Invasive Procedure:
none

History of Present Illness:
This is a ___ yo f with h/o recently diagnosed metastatic cancer of unknown prior presenting with nausea, vomiting, and fever to 101 today. Patient has been vomiting over the past 6 - 8 weeks, since before she was diagnosed with metastatic cancer. She also reports pain over her upper abdomen and has very poor PO intake. She has been feeling progressively weak over this time period. Her vomiting and abdominal pain has not increased from the past weeks, but she just feels more fatigued. She has a chronic non-productive cough as well. No URI symptoms, no urinary complaints. She has been constipated, which improves when she stops her anti-emetics. Last bowel movement was yesterday. She is passing gas. She has lower extremity edema, which has been present for the past several weeks.
Of note, she was supposed to have one of her liver mets biopsied in the past several weeks, but she was taking ibuprofen so the biopsy had to be postponed.

In the ED, initial VS were: 97.6 117 128/74 18 95% RA. Labs were significant for WBC of 18.7, with 77% polys. UA was significant for ketones. Patient received zofran, NS. She had a CXR that showed new left sided opacity that may reflect PNA superimposed on metastatic diseae vs. lymphangiitic spread of cancer. She received vanc and cefepime for pneumonia. Vitals on transfer are: 99.6 110 118/78 20 99%.
Currently, she continues to feel weak and nauseous. She is trying to take her pants off, but feels too weak and tired to do so.

REVIEW OF SYSTEMS:
(+) per HPI
(-) night sweats, headache, vision changes, rhinorrhea, congestion, sore throat, BRBPR, melena, hematochezia, dysuria, hematuria.

History of Present Illness:
This is a ___ yo f with h/o recently diagnosed metastatic cancer of unknown prior presenting with nausea, vomiting, and fever to 101 today. Patient has been vomiting over the past 6 - 8 weeks, since before she was diagnosed with metastatic cancer. She also reports pain over her upper abdomen and has very poor PO intake. She has been feeling progressively weak over this time period. Her vomiting and abdominal pain has not increased from the past weeks, but she just feels more fatigued. She has a chronic non-productive cough as well. No URI symptoms, no urinary complaints. She has been constipated, which improves when she stops her anti-emetics. Last bowel movement was yesterday. She is passing gas. She has lower extremity edema, which has been present for the past several weeks.
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Currently, she continues to f weak and nauseous. She is trying to take her pants off, t feels too weak and tired to do so.

Problem: Data leakage (some notes contain the pathology/finding associated with the x-ray)

History of Present Illness:
This is a ___ yo f with h/o recently diagnosed metastatic cancer of unknown prior presenting with nausea, vomiting, and fever to 101 today. Patient has been vomiting over the past 6 - 8 weeks, since before she was diagnosed with metastatic cancer. She also reports pain over her upper abdomen and has very poor PO intake. She has been feeling progressively weak over this time period. Her vomiting and abdominal pain has not increased from the past weeks, but she just feels more fatigued. She has a chronic non-productive cough as well. No URI symptoms, no urinary complaints. She has been constipated, which improves when she stops her anti-emetics. Last bowel movement was yesterday. She is passing gas. She has lower extremity edema, which has been present for the past several weeks.
Of note, she was supposed to have one of her liver mets biopsied in the past several weeks, but she was taking ibuprofen so the biopsy had to be postponed.

Solution: Extraction of paragraphs that don't contain explanation of results from the ED (via algorithm)

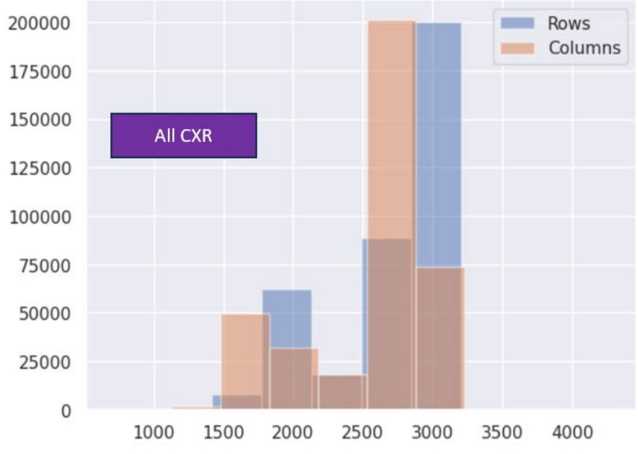
Data Processing – Images

Key challenges with imaging data:

- Patients can have more than 1 X-ray
- X-rays can be taken from multiple angles and positions
- Images are of varying sizes

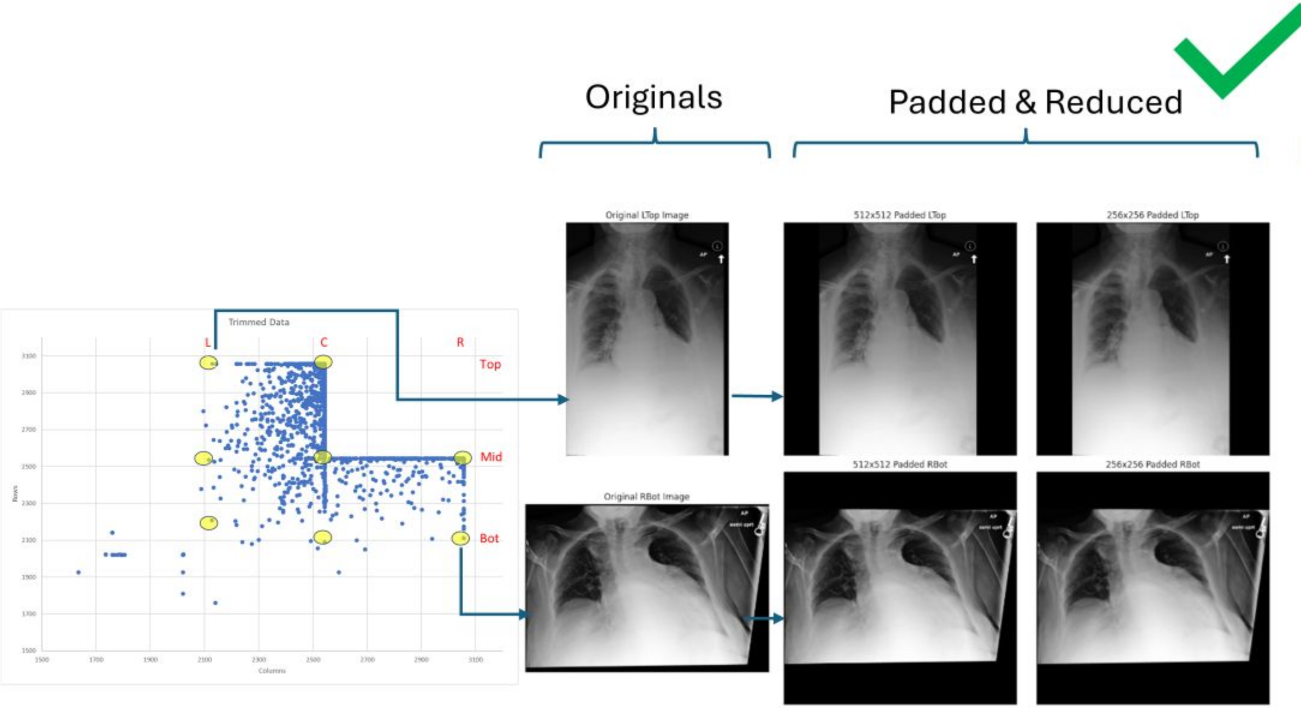
Progress on imaging data:

- Found positioning metadata connected with each image to identify the orientation of the image systematically
- Developed a logic to select which image we will keep from each patient



(in pixels)

Data Processing – Image Padding



Data Processing – Images

Logic for reducing/selecting which image to keep from each patient:

1. For each patient, if # of images per study > 1: [Main criteria for reducing all images per patient down to 1 single image]
2. Non-lateral views are preferred* (from SME conversations)
3. Exclude 'Recumbent' orientation wherever possible
4. Prefer images with larger 'Rows' pixels if orientations vary
5. Latest 'StudyTime' if times vary
6. Remove record with NaN in meta data for two images with similar other meta data
7. Remove record with lower 'Columns' if column pixels is the only difference in the meta data between 2 images
8. Preference to 'antero-posterior' view over 'posterior-antero' if this is the only difference in the meta data

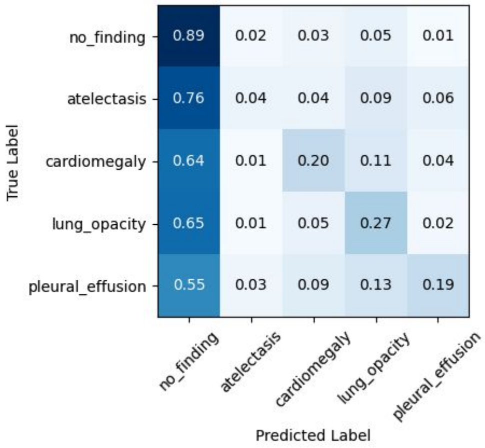
NLP Models - Top Performers

	Train Data	Class Weights	AUC
Bio_ClinicalBERT	Unbalanced	No	0.66531
Bio_ClinicalBERT	Unbalanced	Yes	0.65781
Bio_ClinicalBERT	Balanced	No	0.66177
Bio_Discharge_Summary_BERT	Unbalanced	No	0.61101
Bio_Discharge_Summary_BERT	Unbalanced	Yes	0.51912
Bio_Discharge_Summary_BERT	Balanced	No	0.65772
BioBERT	Unbalanced	No	0.60079
BioBERT	Unbalanced	Yes	0.52576
BioBERT	Balanced	No	0.67084

Top NLP Model (Bio_ClinicalBERT)

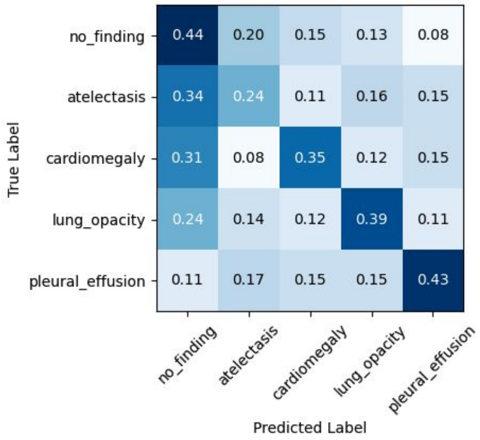
Unbalanced

	precision	recall	f1-score
no_finding	0.77	0.89	0.82
atelectasis	0.15	0.04	0.07
cardiomegaly	0.27	0.20	0.23
lung_opacity	0.35	0.27	0.30
pleural_effusion	0.35	0.19	0.25
accuracy			0.69
macro avg	0.38	0.32	0.33
weighted avg	0.63	0.69	0.65



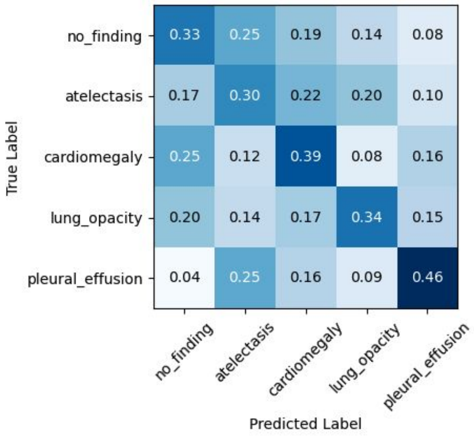
Unbalanced with class weights

	precision	recall	f1-score
no_finding	0.81	0.44	0.57
atelectasis	0.08	0.24	0.12
cardiomegaly	0.15	0.35	0.21
lung_opacity	0.28	0.39	0.32
pleural_effusion	0.18	0.43	0.26
accuracy			0.42
macro avg	0.30	0.37	0.30
weighted avg	0.63	0.42	0.48



Balanced

	precision	recall	f1-score
no_finding	0.82	0.33	0.47
atelectasis	0.08	0.30	0.12
cardiomegaly	0.13	0.39	0.19
lung_opacity	0.24	0.34	0.28
pleural_effusion	0.18	0.46	0.26
accuracy			0.34
macro avg	0.29	0.36	0.26
weighted avg	0.63	0.34	0.40

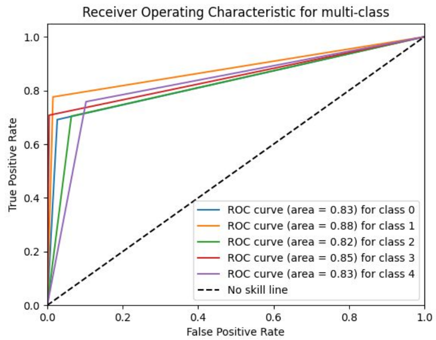


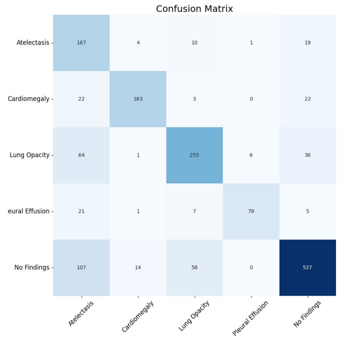
Top Imaging Model: EfficientNet-B3 Results

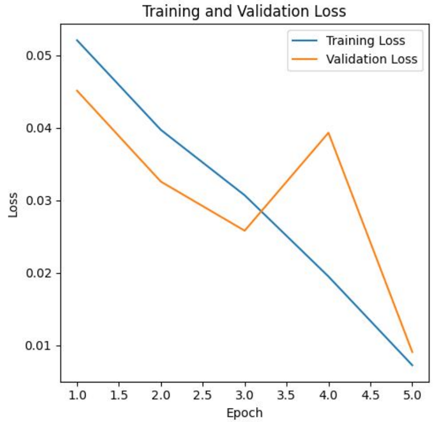
	Precision	Recall	F1-score	**AUC**
Atelectasis	0.79	0.69	0.74	**0.83**
Cardiomegaly	0.89	0.78	0.83	**0.88**
Lung Opacity	0.76	0.70	0.73	**0.82**
Pleural Effusion	0.92	0.71	0.80	**0.85**
No Findings	0.86	0.76	0.80	**0.83**

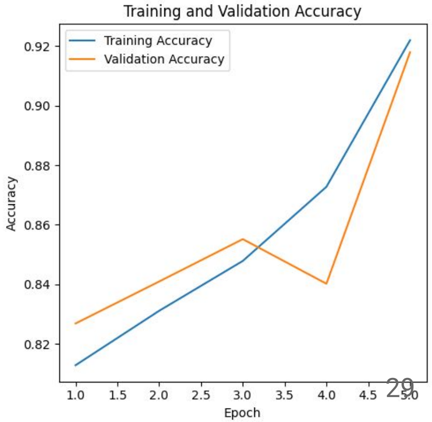
Other computer vision models assessed:

- RestNet18
- DenseNet121
- Various custom CNNs





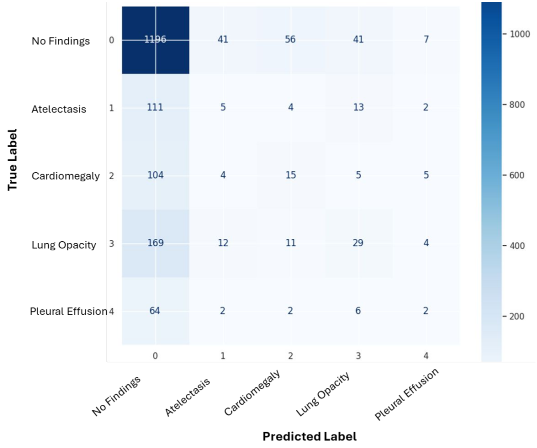




Individual Model Performance

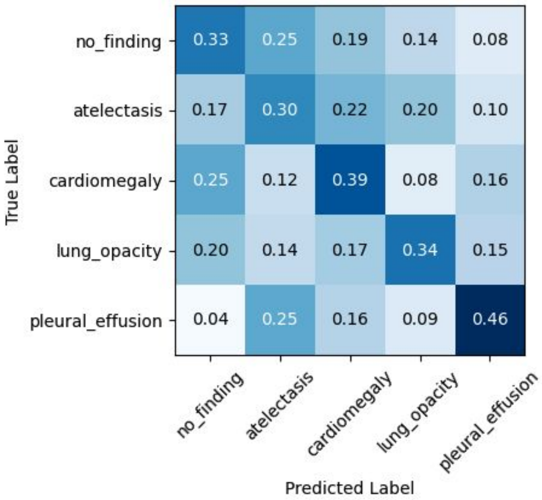
Tabular Model

XGBoost



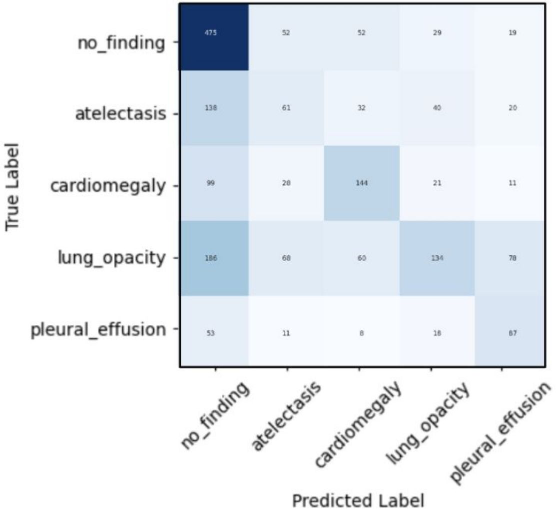
Notes Model

Bio_ClinicalBERT

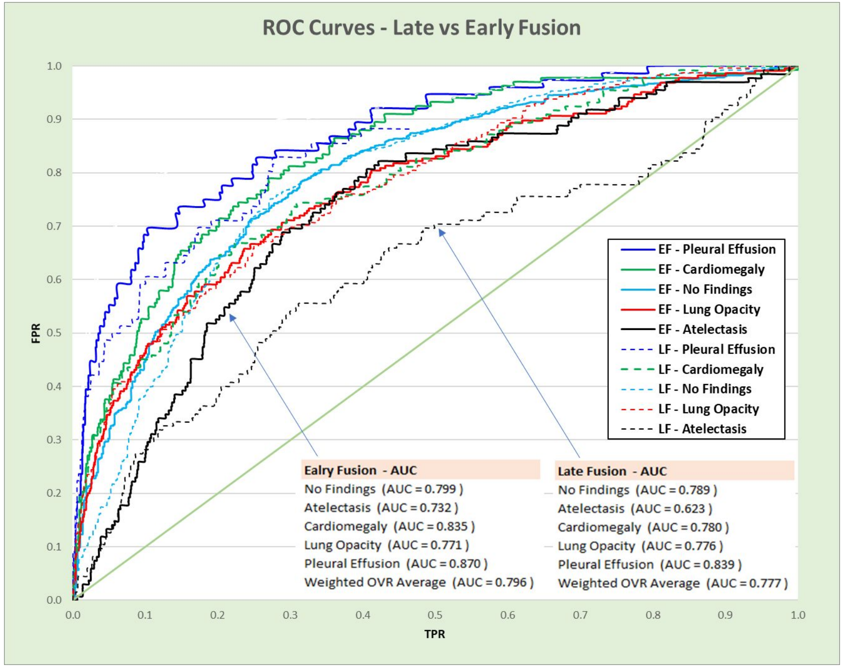


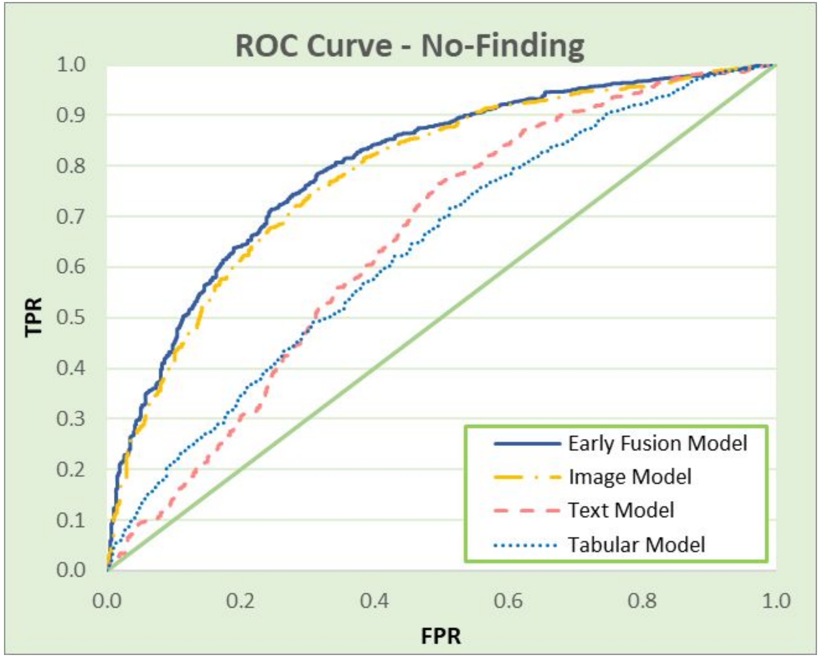
Images Model

EfficientNet-B3

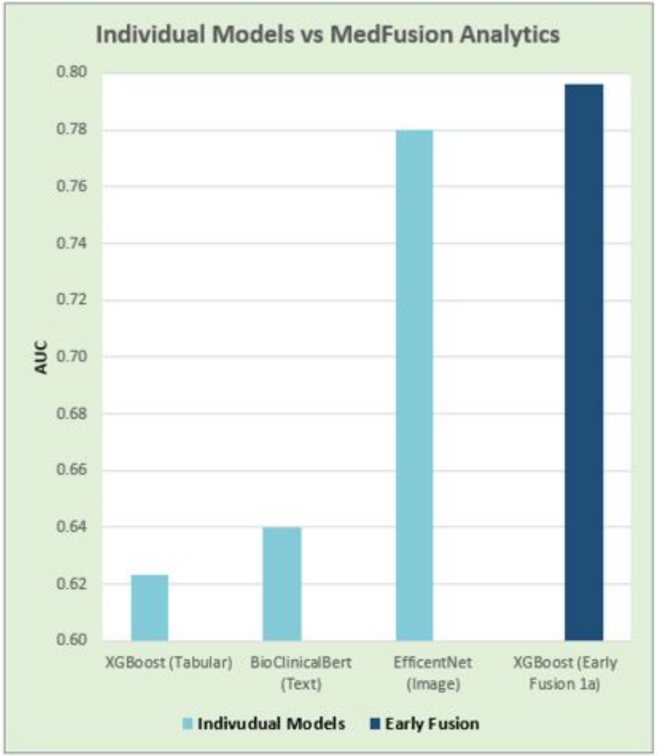


Fusion Model Comparisons – Additional Figures





Average AUC



Research Summary

Case	Model	estimator	basis	data	AUC Score Average	no findings	atelectasis	cardiomegaly	lung opacity	pleural effusion
1	Tabular	XGBoost	train	trainset	0.6617	0.6655	0.6497	0.6777	0.6641	0.6469
			CV	-	0.6024					
			val	valset	0.6215	0.6247	0.5698	0.6260	0.6587	0.5565
			test	**testset**	**0.6234**	**0.6358**	**0.5184**	**0.6140**	**0.6204**	**0.6164**
2	Notes 1	Bert	train	trainset	0.8314	0.8003	0.7226	0.9052	0.8556	0.9257
			val	valset	0.6416	0.6490	0.5247	0.6602	0.6382	0.7007
			test	**testset**	**0.6399**	**0.6491**	**0.5042**	**0.6811**	**0.5994**	**0.7654**
5	Image 2	EfficientNet	train	large modified trainset	0.9964	0.9962	0.9918	0.9989	0.9964	0.9993
			val	valset	0.7759	0.7771	0.7233	0.8226	0.7601	0.8137
			test	**testset**	**0.7799**	**0.7832**	**0.7361**	**0.8080**	**0.7450**	**0.8548**
13	EF 1a: Tabular + Notes1 + Image2	XGBboost	train	trainset + valset	0.9635	0.9526	0.9521	0.9759	0.9586	0.9782
			CV	-	0.9491					
			test	**testset**	**0.7962**	**0.7987**	**0.7319**	**0.8350**	**0.7713**	**0.8705**

Notes:

1 All data are for 4_bal_s (4 pathologies, balanced data, and single pathology per image)

2 All models (except Image model) used the same following datasets

trainset	2118
valset	1940
testset	1930

Research Summary

Case	Model	estimator	basis	data	AUC Score: Average	no findings	atelectasis	cardiomegaly	lung opacity	pleural effusion	Std D	Min	Max
1	Tabular	XGBoost	train	trainset	0.6617	0.6655	0.6497	0.6777	0.6641	0.6469			
			CV	-	0.6024								
			val	valset	0.6215	0.6247	0.5698	0.6260	0.6587	0.5565			
			test	testset	0.6234	0.6358	0.5184	0.6140	0.6204	0.6164			
2	Notes 1	Bert	train	trainset	0.8314	0.8003	0.7226	0.9052	0.8556	0.9257			
			val	valset	0.6416	0.6490	0.5247	0.6602	0.6382	0.7007			
			test	testset	0.6399	0.6491	0.5042	0.6811	0.5994	0.7654			
3	Notes 2	Bert	train	trainset	0.8757	0.8399	0.8019	0.9303	0.9081	0.9494			
			val	valset	0.6496	0.6549	0.5137	0.6634	0.6666	0.7300			
			test	testset	0.6500	0.6598	0.4766	0.6547	0.6583	0.7531			
4	Image 1	CNN	train	trainset	0.4971	0.4930	0.4978	0.4955	0.5038	0.4996			
			val	valset	0.5009	0.5038	0.5004	0.4849	0.4934	0.4994			
			test	testset	0.5032	0.5061	0.5001	0.4997	0.4903	0.5016			
5	Image 2	EfficientNet	train	large modified trainset	0.9964	0.9962	0.9918	0.9989	0.9964	0.9993			
			val	valset	0.7759	0.7771	0.7233	0.8226	0.7601	0.8137			
			test	testset	0.7799	0.7832	0.7361	0.8080	0.7450	0.8548			
6	Tabular + Image (CNN)	XGBboost	train	trainset+valset	0.4985	0.4931	0.4986	0.4969	0.5040	0.4997			
			CV	-	0.6130						0.0068	0.5983	0.6216
			test	testset	0.6315	0.6395	0.5456	0.6288	0.6486	0.5980			
7	Tabular + Notes 1	XGBboost	train	trainset+valset	0.8294	0.7921	0.7557	0.8650	0.8359	0.8983			
			CV	-	0.7892						0.0143	0.7634	0.8109
			test	testset	0.6830	0.6909	0.5564	0.6983	0.6685	0.7842			
8	Tabular + Notes 2	XGBboost	train	trainset+valset	0.8362	0.7909	0.7562	0.8789	0.8436	0.9113			
			CV	-	0.8128						0.0128	0.7914	0.8325
			test	testset	0.6691	0.6735	0.5193	0.6752	0.7048	0.7406			
9	Late Fusion	-	train	trainset+valset	0.8248	0.9181	0.8968	0.9646	0.9523	0.9744			
			CV	-	0.6823						0.0126	0.7951	0.8394
			test	testset	0.6844	0.6929	0.5770	0.6923	0.6746	0.7414			
10	EF 1a: Tabular + Note2 + Image1	XGBboost	train	trainset+valset	0.8624	0.8242	0.7999	0.8966	0.8713	0.9201			
			CV	-	0.8196						0.0126	0.7951	0.8394
			test	testset	0.6732	0.6794	0.5029	0.6962	0.7020	0.7423			
11	EF 1a: Tabular + Notes2 + Image 2	XGBboost	train	trainset + valset	0.9634	0.9525	0.9515	0.9768	0.9569	0.9791			
			CV	-	0.9506						0.0066	0.9433	0.9613
			test	testset	0.7929	0.7952	0.7308	0.8258	0.7762	0.8553			
12	EF 1b: Tabular + Notes2 + Image2	XGBboost	train	trainset + valset	0.9624	0.9509	0.9497	0.9759	0.9553	0.9805			
			CV	-	0.9511						0.006203148	0.9428239	0.9605757
			test	testset	0.7920	0.7951	0.7264	0.8258	0.7719	0.8536			
13	EF 1a: Tabular + Notes1 + Image2	XGBboost	train	trainset + valset	0.9635	0.9526	0.9521	0.9759	0.9586	0.9782			
			CV	-	0.9491						0.0071	0.9394764	0.9608
			test	testset	0.7962	0.7987	0.7319	0.8350	0.7713	0.8705			
14	Image 3	EfficientNet	train	trainset									
			val	valset									
			test	testset	0.7621	0.7655	0.6960	0.8167	0.7097	0.8787			
15	EF 1a: Tabular + Notes2 + Image3	XGBboost	train	trainset + valset	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000			
			CV	-	0.9900						0.0016	0.9876094	0.9921
			test	testset	0.7635	0.7661	0.6724	0.7916	0.7449	0.8844			

Notes:

1 All data are for 4_bal_s (4 pathologies, balanced data, and single pathology per image)

2 All models (except Image model) used the same following datasets

trainset	2118
valset	1940
testset	1930

3 train/test records ratio is different for different cases!

Research Summary