

# Bootstrapping Chest CT Image Understanding by Distilling Knowledge from X-ray Expert Models

## Supplementary Material

### 6. Extraction of pathology entities

We utilized the CheXpert labeling tool [16] to identify six pathologies within the reports. For each CT report, specific keywords were used to pinpoint six different pathologies, detailed in Table 5. The frequency of each pathology in the ChestCT-16K and ChestCT-EXT datasets is summarized in Table 6.

Pythology	Related key words
Nodule	nodule, nodules, nodular
Opacity	opacity, opacities, decreased translucency, increased density, airspace disease, air-space disease, air space disease, infiltrate, infiltration, interstitial marking, interstitial pattern, interstitial lung, reticular pattern, reticular marking, reticulation, parenchymal scarring, peribronchial thickening, wall thickening, scar
Pleural Effusion	pleural fluid, pleural effusion
Emphysema	emphysema
Inflammation	inflammation, pneumonia, infection, infectious process, infectious
Calcification	calcification, calcifications

Table 5. Keywords for extracting six pathologies.

Pythology	ChestCT-16K			ChestCT-EXT
	Train	Val	Test	Test
Nodule	8084	923	1894	1689
Opacity	6559	757	1489	1347
Pleural Effusion	536	65	120	147
Emphysema	522	57	95	221
Inflammation	1244	139	303	220
Calcification	1826	182	384	290

Table 6. The number of six entities in the ChestCT-16K and ChestCT-EXT datasets.

### 7. Comparison of different report generation methods using NLP metrics

Table 7 shows the NLP evaluation of our method, consistently outperforming other competitors across all NLP metrics, not only on the internal test set, ChestCT-16K, but also on the external test set, ChestCT-EXT.

Methods	BLEU-4	METEOR	ROUGE-L	CIDEr
Internal test: ChestCT-16K				
R2Gen [5]	7.3	10.4	28.3	7.8
CMN [6]	5.6	8.6	25.5	5.2
RadFM [36]	0.1	4.3	8.6	1.5
BLIP [22]	13.2	19.4	37.9	21.1
DCL [23]	12.5	18.6	37.1	19.0
Ours	<b>13.8</b>	<b>21.3</b>	<b>40.2</b>	<b>24.4</b>
External test: ChestCT-EXT				
R2Gen [5]	6.9	10.8	27.1	3.7
CMN [6]	3.2	7.2	21.3	1.7
RadFM [36]	0.1	0.7	1.6	0.2
BLIP [22]	11.2	16.7	33.8	9.6
DCL [23]	10.6	16.4	33.6	9.9
Ours	<b>12.0</b>	<b>17.6</b>	<b>35.4</b>	<b>10.7</b>

Table 7. Comparison of NLP metrics of different methods in the ChestCT-16K test set and ChestCT-EXT dataset.

### 8. Comparison of entity-focused masking (EFM) and random masking

Figure 7 illustrates random masking and the proposed EFM. The panel ‘A’ displays the original report, while the panel ‘B’ illustrates the tokenized report using the BERT tokenizer [9], with the ‘##’ symbol indicating the sub-word of the previous one. In the panel B, the highlighted entities are marked in yellow, and the attributes of these entities, such as location, are highlighted in green. The panels ‘C1’, ‘C2’, and ‘C3’ demonstrate examples of the report with tokens randomly masked (indicated by red highlights), compared to the panels ‘D1’, ‘D2’, and ‘D3’, which utilize the EFM for selective masking of reports. The illustration makes it clear that the random masking may obscure words like ‘lung’ or ‘thick’ that could be guessed from the surrounding text, whereas EFM masks either an entity or its attributes. This encourages the model to rely more heavily on visual clues from the associated images to predict the masked information.

### 9. An example of language-guided retrieval

In Figure 8, we present a detailed example of a language-guided retrieval process, which includes a CT query report and the nine most similar X-ray reports. The X-ray report with the highest degree of similarity has a score of 0.963. Symptoms of pleural effusion are present in both of the



Report similarity score

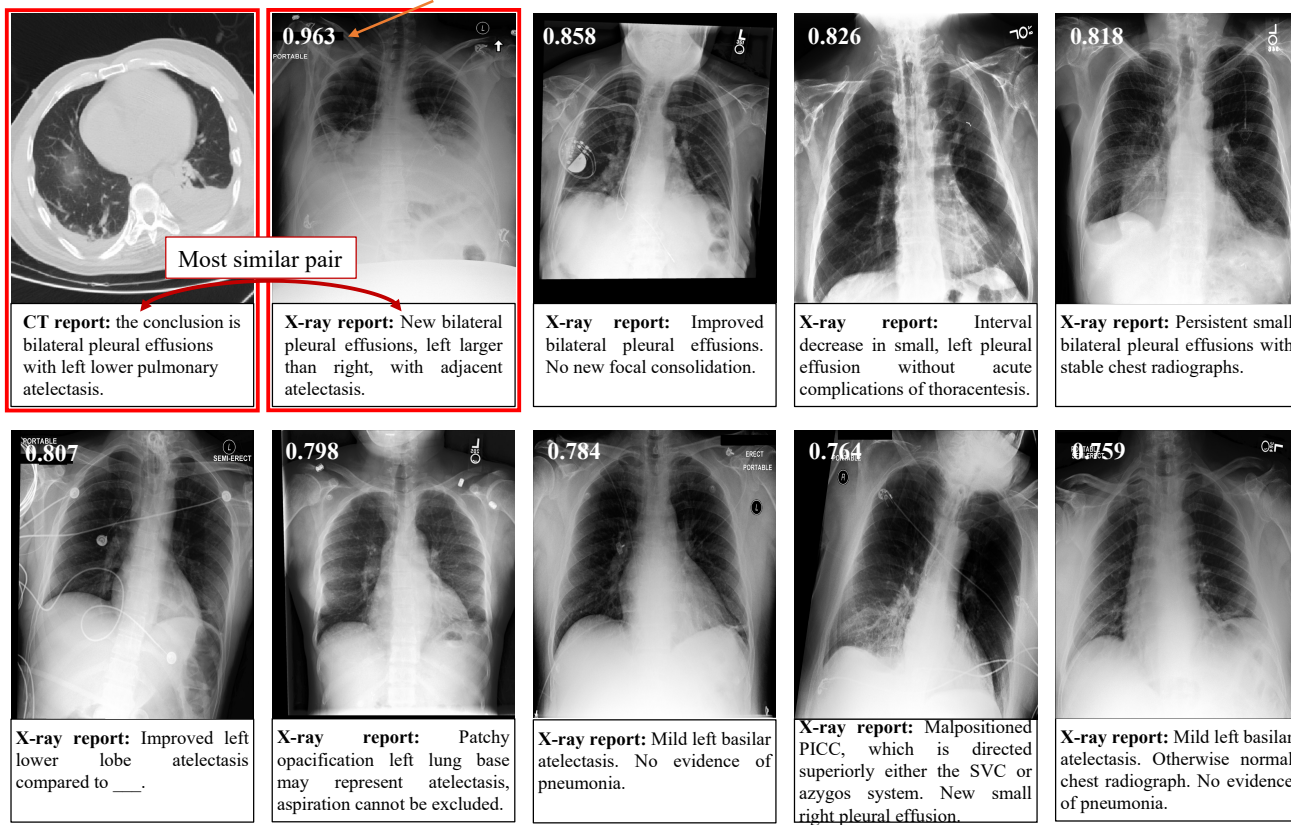


Figure 8. An example of language-guided report retrieval.