



Enhanced Contrastive Learning with Multi-view Longitudinal Data for Chest X-ray Report Generation



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-Introduction

Motivation

- In clinical practice, radiologists integrate patients' symptoms with current multi-view imaging studies to assess disease status. Simultaneously, they may consider medical history to evaluate disease progression, enhancing diagnostic accuracy.
- Most methods rely on **single-view images**, limiting diagnostic accuracy and ignoring disease progression. Even with longitudinal data, current visits are still analyzed using single images.

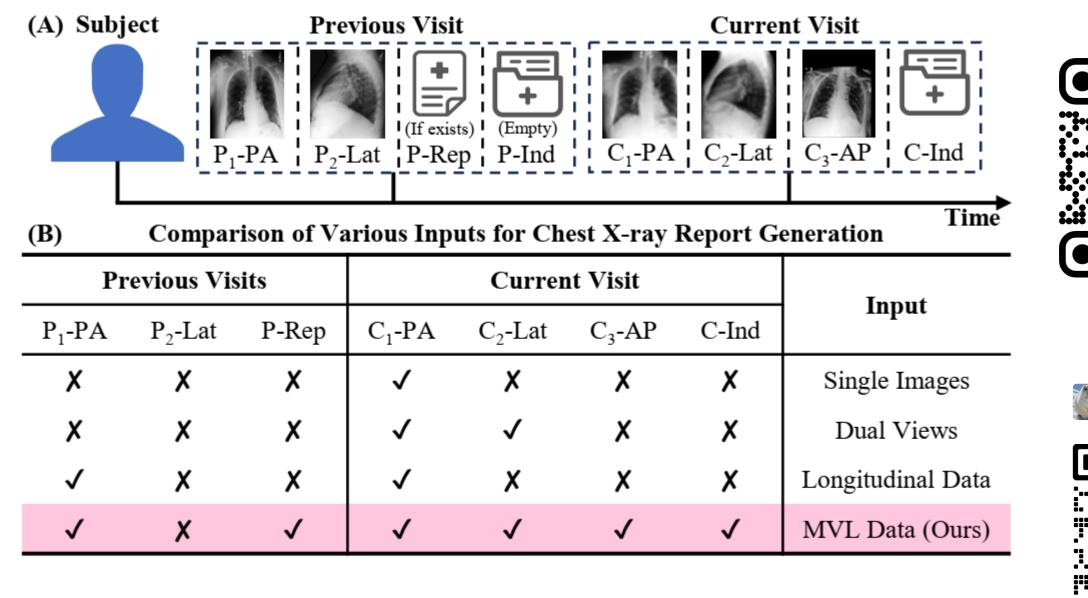


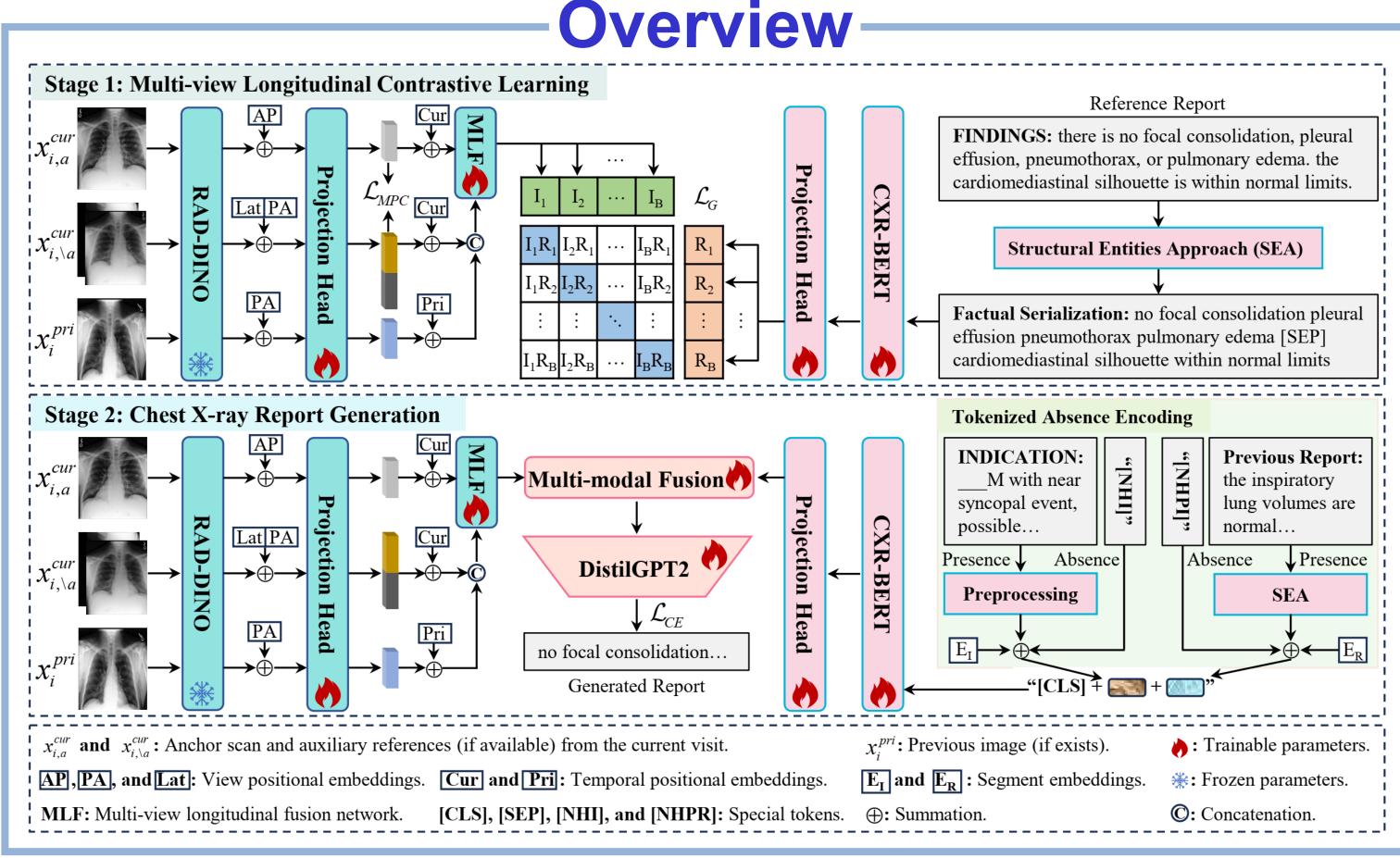
Figure 1. (A) shows medical historical data of a subject (patient) over time. (B) compares inputs for RRG, with AP and PA as frontal views, and Lat and Rep as a lateral view and its report. Ind and MVL Data are "INDICATION" and multi-view longitudinal data.

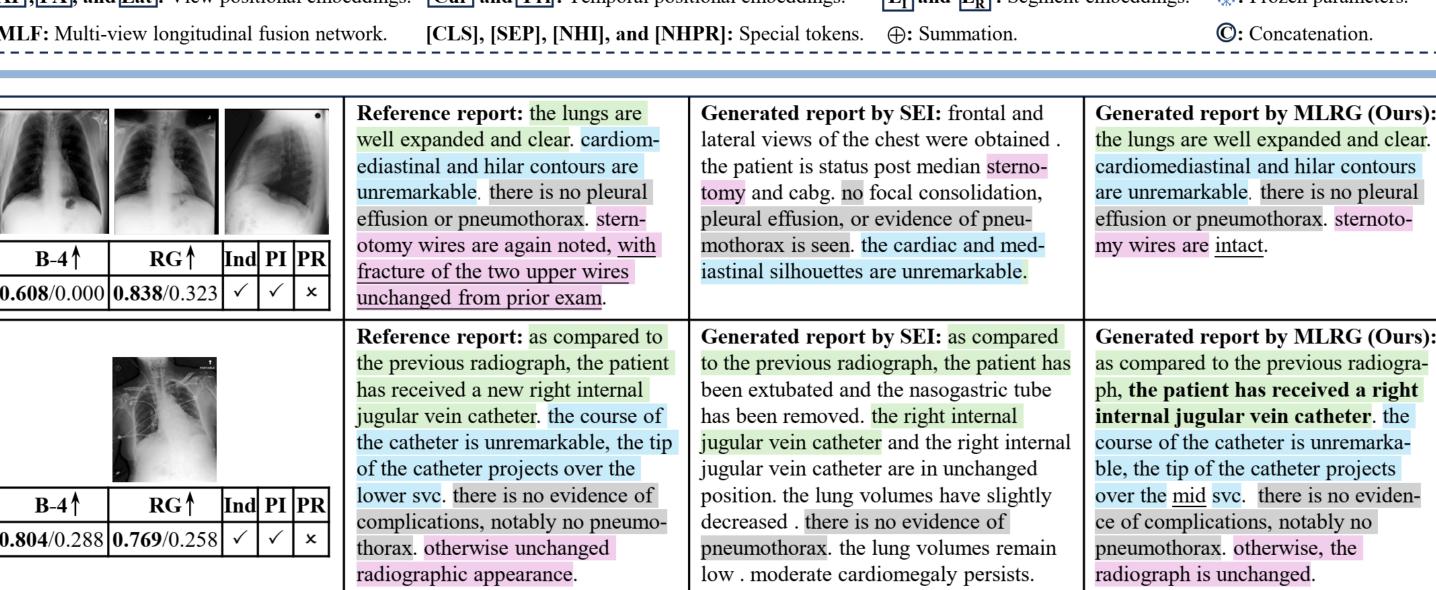


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Contribution

- We propose a novel multi-view longitudinal contrastive learning method that **flexibly integrates multi-view longitudinal (MVL)** data and leverages inherent spatiotemporal information from reports to supervise the pre-training of visual and textual representations.
- We introduce a **tokenized absence encoding technique** to handle missing patient-specific prior knowledge, enabling flexible adaptation to scenarios with or without such data.





-Summary

- MLRG captures inter-view differences and extracts spatial features from current multiview images and temporal features from longitudinal data, effectively leveraging reportbased spatiotemporal cues for pre-training. We further introduce a tokenized absence encoding technique to handle missing patient-specific prior knowledge.
- MLRG achieves a +2.3% BLEU-4 on MIMIC-CXR, +5.5% F1-CheXbert on MIMIC-ABN, and +2.7% F1-RadGraph on Two-view CXR).
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- Code: https://github.com/mk-runner/MLRG

Experiments

Dataset	Input	Method	Venue	NLG Metrics ↑						CE Metrics ↑			
Dataset	Input	Witting	venue	B-1	B-2	B-3	B-4	MTR	R-L	RG	P	R	F1
	SI	SA [56]	EMNLP'23	-	0.184	-	-	-	-	0.228	-	-	0.394
	SI	MET [53]	CVPR'23	0.386	0.250	0.169	0.124	0.152	0.291	-	0.364	0.309	0.311
	SI	KiUT [17]	CVPR'23	0.393	0.243	0.159	0.113	0.160	0.285	-	0.371	0.318	0.321
	SI	CoFE [26]	ECCV'24	-	-	-	0.125	0.176	0.304		0.489	0.370	0.405
M-CXR	SI	MAN [42]	AAAI'24	0.396	0.244	0.162	0.115	0.151	0.274	-	0.411	0.398	0.389
	SI	B-LLM [28]	AAAI'24	<u>0.402</u>	<u>0.262</u>	<u>0.180</u>	0.128	<u>0.175</u>	0.291	-	0.465	0.482	<u>0.473</u>
	SI	DCG [27]	ACMMM'24	0.397	0.258	0.166	0.126	0.162	0.295	-	0.441	0.414	0.404
	SI	Med-LLM [31]	ACMMM'24	-	-	-	0.128	0.161	0.289	-	0.412	0.373	0.395
	SI+Ind	SEI [29]	MICCAI'24	0.382	0.247	0.177	<u>0.135</u>	0.158	0.299	0.249	0.523	0.410	0.460
	MVD	FMVP [32]	TMM'23	0.389	0.236	0.156	0.108	0.150	0.284	-	0.332	0.383	0.336
	Long	HERGen [49]	ECCV'24	0.395	0.248	0.169	0.122	0.156	0.285	-	-	-	-
	MVL	CXRMate [36]	arXiv'23	0.361	0.223	0.150	0.108	0.159	0.263	0.238	0.495	0.367	0.422
	MVL	MLRG(Ours)	-	0.411	0.277	0.204	0.158	0.176	0.320	0.291	0.549	<u>0.468</u>	0.505
	-	Δ (%) \uparrow	-	+0.9	+1.5	+2.4	+2.3	+0.1	+1.6	+4.2	+2.6	-1.4	+3.2
	SI	R2Gen [♭] [8]	EMNLP'20	0.253	0.144	0.092	0.063	0.106	0.229	0.179	0.444	0.425	0.434
	SI	CMN^{\flat} [9]	ACL'21	0.256	0.147	0.095	0.066	0.110	0.230	0.183	0.466	<u>0.454</u>	0.460
M-ABN	SI+Ind	SEI [♭] [29]	MICCAI'24	0.267	0.157	0.104	0.073	<u>0.114</u>	0.231	0.191	0.466	0.408	0.435
	MVL	MLRG(Ours)	-	0.332	0.199	0.132	0.094	0.136	0.248	0.219	0.513	0.517	0.515
	-	Δ (%) \uparrow	-	+6.5	+4.2	+2.8	+2.1	+2.2	+1.7	+2.8	+4.7	+6.3	+5.5
	DV	R2Gen [♭] [8]	EMNLP'20	0.346	0.219	0.153	0.113	0.141	0.302	0.267	0.478	0.329	0.390
	DV	CMN^{\flat} [9]	ACL'21	0.387	0.241	0.166	0.122	0.151	0.310	0.268	0.496	0.336	0.401
T-CXR	DV+Ind	SEI [♭] [29]	MICCAI'24	0.409	0.263	0.186	0.140	0.168	0.320	0.301	0.522	0.447	0.390 0.401 0.481
	MVL	MLRG(Ours)	-	0.417	0.276	0.200	0.154	0.178	0.331	0.328	0.532	0.474	0.501
	-	Δ (%) \uparrow	-	+0.8	+1.3	+1.4	+1.4	+1.0	+1.1	+2.7	+1.0	+2.7	+2.0

Model	M/S	F/R	ΡI	Stage 1		Stage 2		NLG metrics ↑						CE metrics ↑	
1/10401	1,10	1/10		$\overline{\mathcal{L}_G}$	\mathcal{L}_{MPC}	Ind	PR	B-1	B-2	B-3	B-4	MTR	R-L	RG	F1
(a)	M	F	✓	X	X	✓	✓	0.346	0.235	0.173	0.136	0.154	0.305	0.258	0.373
(b)	M	F	✓	✓	\checkmark	X	X	0.385	0.239	0.162	0.118	0.155	0.283	0.238	0.479
(c)	M	F	X	✓	X	✓	✓	0.384	0.257	0.188	0.146	0.165	0.310	0.267	0.455
(d)	M	F	X	✓	\checkmark	✓	✓	0.395	0.257	0.183	0.138	0.167	0.302	0.278	0.503
(e)	M	F	✓	✓	✓	✓	X	0.392	0.265	0.195	0.153	0.171	0.316	0.281	0.476
(f)	M	F	✓	✓	✓	X	✓	0.387	0.240	0.163	0.118	0.156	0.281	0.243	0.484
(g)	M	R	✓	✓	✓	✓	✓	0.403	0.267	0.193	0.148	0.172	0.309	0.287	0.510
(h)	S	F	✓	✓	X	✓	✓	0.400	0.269	0.196	0.151	0.173	0.314	0.289	0.498
MLRG	M	F	✓	✓	✓	✓	✓	0.411	0.277	0.204	0.158	0.176	0.320	0.291	0.505

Table 3. Ablation study on the MIMIC-CXR dataset. "M/S" refers to methods that utilize current Multi-view images or Single images as input. "F/R" indicates alignment based on either Factual serialization or Report. "PI", "PR", and "Ind" represent Previous Images, Previous Reports, and "INDICATION", respectively. The best values are emphasized in **bold**.

Setting	%	B-2 ↑	B-4 ↑	MTR ↑	R-L↑	RG ↑
w/ Ind	57.8	0.295	0.174	0.184	0.332	0.318
w/o Ind	42.2	0.253	0.137	0.166	0.302	0.254
w/ MV	70.7	0.282	0.161	0.179	0.323	0.301
w/o MV	29.3	0.264	0.150	0.171	0.310	0.266
w/ MVL	61.4	0.282	0.160	0.178	0.322	0.300
w/o MVL	38.6	0.270	0.155	0.174	0.316	0.276

Table 4. Breakdown of MLRG's metrics on the MIMIC-CXR test set, categorized by (a) inclusion of indications (Ind), (b) inclusion of current multi-view images (MV), (c) inclusion of multi-view longitudinal data (MVL).

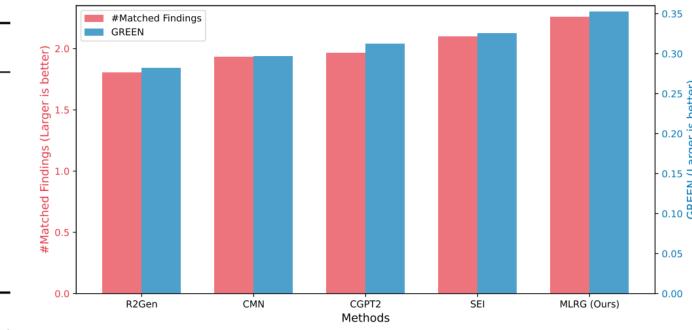


Figure 5. Comparison with baselines on MIMIC-CXR using LLMs. "#Matched Findings" denotes the number of matched findings between generated and reference reports.