

Learning to Exploit Temporal Structure for Biomedical Vision–Language Processing

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Abstract

Self-supervised learning in vision–language processing (VLP) exploits semantic alignment between imaging and text modalities. Prior work in biomedical VLP has mostly relied on the alignment of single image and report pairs even though clinical notes commonly refer to prior images. This does not only introduce poor alignment between the modalities but also a missed opportunity to exploit rich self-supervision through existing temporal content in the data. In this work, we explicitly account for prior images and reports when available during both training and fine-tuning. Our approach, named BioViL-T, uses a CNN–Transformer hybrid multi-image encoder trained jointly with a text model. It is designed to be versatile to arising challenges such as pose variations and missing input images across time. The resulting model excels on downstream tasks both in single- and multi-image setups, achieving state-of-the-art (SOTA) performance on (I) progression classification, (II) phrase grounding, and (III) report generation, whilst offering consistent improvements on disease classification and sentence-similarity tasks. We release a novel multi-modal temporal benchmark dataset, MS-CXR-T, to quantify the quality of vision–language representations in terms of temporal semantics. Our experimental results show the advantages of incorporating prior images and reports to make most use of the data.

1. Introduction

Self-supervision from image–text pairs has enabled the development of flexible general-purpose vision–language models both in the general domain [40, 53, 77] and for specialised domains such as biomedicine and radiology

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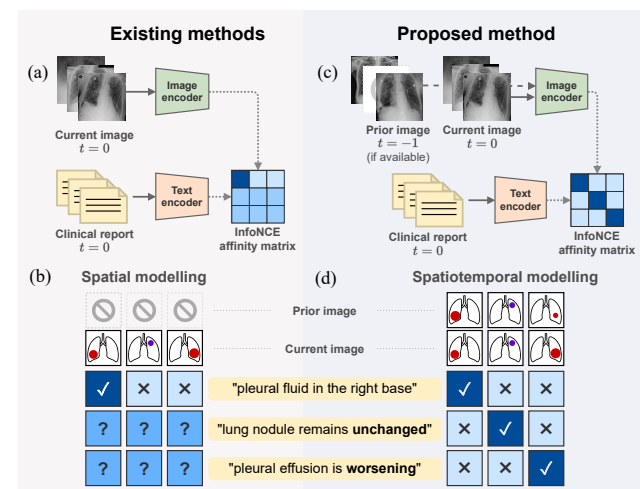


Figure 1. (a) Existing visual–language pre-training approaches [9, 32, 81] often use only a single image for contrastive learning (e.g., InfoNCE [49]). (b) In such settings, discarding the temporal connectivity of images limits the alignment of image–text pairs as shown with the affinity matrix, leading to suboptimal pre-training and missed opportunity to create additional model supervision for free. (c, d) Our approach exploits this domain knowledge by learning to incorporate a series of images and correlate them to reports, leading to pre-trained models that can generalise to a wider range of downstream tasks whilst achieving SOTA performance.

[9, 32, 81]. Vision–language processing (VLP) has shown that cross-modal supervision can provide a richer signal for training both image [19] and text [9] models. However, the success of VLP relies on paired samples sharing semantics, i.e., given an image and text pair, the text should describe the image with minimal extraneous detail [15, 16, 35].

In this regard, VLP in biomedicine and radiology poses a distinctive challenge, as reports routinely include comparisons to prior imaging studies [3, 47, 57]. Without knowl-

edge of this prior image¹, temporal information in the text modality, e.g. “Pneumonia is improving”, could pertain to any image containing “Pneumonia”, producing ambiguity during contrastive training (Figure 1). Despite this, the existing VLP work to date considers alignment between only single images and reports [9,32,46,81], going so far as to remove temporal content from reports in training data to prevent ‘hallucinations’ in downstream report generation [54]. However, temporal information can provide complementary self-supervision, solely by exploiting existing structure, and without requiring any additional data.

In this work, we neither ignore nor remove temporal information in the text modality, but explicitly account for it during pre-training. Rather than treating all image–report pairs in the dataset as independent, we exploit temporal correlations by making prior images available for comparison to a given report. To learn from this structure, we develop a temporal VLP pre-training framework named *BioViL-T*. A core component is its new multi-image encoder that can handle the absence of prior images and potential spatial misalignment between images across time. *BioViL-T* takes into account prior images where available, removing cross-modal ambiguity as illustrated in Fig. 1. Linking multiple images during pre-training proves beneficial to both image and text models: we report state-of-the-art (SOTA) performance on both temporal image classification and report generation. In the latter case, we show that prefixing the prior *report* substantially increases performance, again reflecting the value of prior information. We emphasise that the benefit is not restricted to temporal downstream tasks: our approach also achieves SOTA on non-temporal tasks of pneumonia detection [60] and phrase grounding [10], underscoring the value of a cleaner learning signal during VLP without needing to modify or add to the training dataset. Our contributions can be summarised as follows:

- We introduce a novel pre-training framework called *BioViL-T*. It leverages the temporal relationship of samples to self-supervise VLP models, making commonly used biomedical VLP models (e.g., [9,32,81]) more applicable to a wider range of downstream tasks without compromising performance on existing benchmarks.
- We develop a generic multi-image encoder that handles missing image inputs and incorporates longitudinal information without requiring explicit image registration.
- We achieve SOTA results in chest X-ray (CXR) report generation, temporal image classification, and phrase grounding downstream benchmarks by accounting for prior context in self-supervised training and fine-tuning.
- We release a new multimodal benchmark dataset, *MS-CXR-T*, curated by an expert radiologist. It enables

¹In the MIMIC-CXR v2 dataset [36], around 40% of reports explicitly reference a previous image. See Appendix B for details.

benchmarking of CXR VLP models in terms of temporal semantics extracted from image and text data.

2. Related work

Vision–language processing Self-supervised VLP can significantly reduce the need for manual labels required for the training of image encoders [19,53]. The availability of large-scale paired image–text datasets has thus led to rapid development of general-purpose VLP models. Objectives include contrastive and discriminative image–text matching [40,53,69] including local variants [32,76], auto-regressive (AR) captioning [4,39,77] and multi-modal masked modelling objectives [13,40,61].

Biomedical vision–language processing Paired medical image–report datasets were originally used for supervised learning via (typically) automated label extraction from clinical reports [33,63,70]. Using such datasets, advances in general-domain *self-supervised* VLP have been demonstrated to benefit biomedical imaging applications [9,32,81]. Work has incorporated ideas from general-domain VLP such as the original CLIP-style cross-modal contrastive objective [81], multi-modal masking with merged co-attention on image–text representations [46], and adaptations to the data of the domain. For example, a radiology report may have sparse image-specific details, prompting a local modification to the contrastive loss enabling alignment between text tokens and image patches [32]. Domain-specific pre-training of the text model is shown to benefit biomedical VLP [9], and preferential masking of medical terms during masked language modelling (MLM) was explored [75]. Here we use a local loss and domain-specific pre-training of the text model, but did not find a benefit to preferential masking. Similarly, cross-attention [22] is used rather than merged co-attention for image-guided MLM.

Longitudinal modelling of medical images While prior images are used in unimodal *supervised* longitudinal analysis of medical images [37,58,68,74], temporal information has not directly been employed for self-supervision. The closest work exploits patient metadata to select positive or negative examples in unimodal contrastive learning [67,79].

Existing models typically employ either late fusion of global image representations [58,64,68,74], which can miss fine-grained localised changes [32], or explicit spatial correspondence of features, using fixed spatial grids [48] or object detection [37]. Registering image pairs is commonly used for change detection in other contexts [17,52,59], and has been applied to medical imaging [5,23]. For CXRs however, registration entails the ill-posed problem of aligning 2D projections of 3D geometry, which inevitably results in residual misalignment. Our approach does not rely on bounding boxes or explicit graph construction as it uses

self-attention of visual tokens across time to handle any spatial misalignment.

Self-supervision across time Self-supervision has found applications on densely-sampled time series data (e.g., video) to capture temporal information [30, 55, 78, 80]. Our problem setting involves sparsely and sporadically sampled data where temporal pretext tasks are less applicable [2]. Similarly, it requires text supervision to enable both static and temporal learning, when temporal structure is present.

3. BioViL-T training framework

Our approach comprises a multi-image encoder designed to extract spatio-temporal features from sequences of images (Section 3.1) and a text encoder incorporating optional cross-attention on image features. The models are trained jointly with image-guided MLM and cross-modal global and local contrastive objectives (Section 3.2). The resulting image and text models are later adapted for uni- or multi-modal downstream tasks as described in Section 3.3. Implementation details are presented in Appendices E and F.

For a given image and report pair $(\mathbf{x}_{\text{img}}^{\text{curr}}, \mathbf{x}_{\text{txt}}^{\text{curr}})$, the report $\mathbf{x}_{\text{txt}}^{\text{curr}}$ describes the current image content and changes in reference to prior images. Our proposed formulation focuses on a single prior image; however, it can be generalised to *multiple* prior images depending on the application. Hence, we construct datasets by including the prior image whenever it exists²: $(\mathbf{x}_{\text{img}}^{\text{curr}}, \mathbf{x}_{\text{img}}^{\text{prior}}, \mathbf{x}_{\text{txt}}^{\text{curr}}) \in \mathcal{D}_m$ or $(\mathbf{x}_{\text{img}}^{\text{curr}}, \emptyset, \mathbf{x}_{\text{txt}}^{\text{curr}}) \in \mathcal{D}_s$ with the resulting dataset being a union of single and multi-image examples: $\mathcal{D} = \mathcal{D}_m \cup \mathcal{D}_s$.

3.1. Extracting spatio-temporal image features

Clinical findings are often observed across different image regions and co-occur simultaneously, which requires dense level visual reasoning across time to capture both static and temporal features. In contrast to late global fusion [64] and bounding-box based approaches [37], BioViL-T leverages local correspondences between image regions across time using transformer self-attention blocks [21]. Thus our method does not require an explicit image registration step between time points.

We propose a hybrid CNN–Transformer encoder model due to its data efficiency and spatial flexibility of cross-attention across time points: $E_{\text{img}} : \mathbb{R}^{W \times H} \rightarrow \mathbb{R}^{W' \times H' \times D_{\text{img}}}$ (e.g., ResNet-50 [31]) and $A_{\text{img}} : \mathbb{R}^{T \times L \times D_{\text{img}}} \rightarrow \mathbb{R}^{L \times D_{\text{img}}}$ (e.g., transformer [21]), where W , H , and T correspond to spatiotemporal dimensions, $L = W'H'$ is the number of visual tokens per image, and D_{img} is the embedding dimension. Here E_{img} serves as a stem network [51] to provide visual token features of individual images. The CNN’s inductive biases [24, 51] en-

²The prior *report* is not included during pre-training as it may further reference an earlier study, reintroducing temporal ambiguity.

sure data efficiency of our hybrid model, making it ideal for smaller scale biomedical datasets. E_{img} is initialised with BioViL weights [9]. The main purpose of A_{img} is to capture patch embedding interactions across time when a prior image $\mathbf{x}_{\text{img}}^{\text{prior}}$ is available and to aggregate them into a fixed-length token representation. Input visual tokens, $\mathbf{H}_0^{\text{curr}} = \mathbf{P}^{\text{curr}} := E_{\text{img}}(\mathbf{x}_{\text{img}}^{\text{curr}})$, $\mathbf{H}_0^{\text{prior}} := E_{\text{img}}(\mathbf{x}_{\text{img}}^{\text{prior}})$ are augmented with spatio-temporal positional encodings and flattened across the spatial dimensions. They are then processed by K transformer encoder [66] layers A as follows:

$$\begin{bmatrix} \mathbf{H}_k^{\text{curr}} \\ \mathbf{H}_k^{\text{prior}} \end{bmatrix} = A_k \left(\begin{bmatrix} \mathbf{H}_{k-1}^{\text{curr}} + \mathbf{S} + \mathbf{1}_L \otimes \mathbf{t}^{\text{curr}} \\ \mathbf{H}_{k-1}^{\text{prior}} + \mathbf{S} + \mathbf{1}_L \otimes \mathbf{t}^{\text{prior}} \end{bmatrix} \right), \quad (1)$$

for $k = 1, \dots, K$, where $\mathbf{S} \in \mathbb{R}^{L \times D_{\text{img}}}$ denotes 2D sinusoidal positional encodings [12] and $\mathbf{T} = [\mathbf{t}^{\text{curr}}; \mathbf{t}^{\text{prior}}] \in \mathbb{R}^{2 \times D_{\text{img}}}$ is its temporal counterpart, which is learnt (Fig. 2) [4]. The layer-normalised (LN) [6] output of the final transformer encoder block $\mathbf{P}^{\text{diff}} := \text{LN}(\mathbf{H}_K^{\text{curr}})$ is an ‘aggregated’ representation of patch-level progression information anchored on the current image. Figure 3 shows attention roll-out [1] applied to \mathbf{P}^{diff} after pre-training, showing how the prior image contributes to the fused representation. Figure A.3 further highlights the robustness to variations in pose underlining that registration is not necessary for this encoder.

Static-temporal feature decomposition When a prior image is available the final image representation $\mathbf{V} := \mathbf{P}^{\text{curr}} \oplus \mathbf{P}^{\text{diff}} \in \mathbb{R}^{W' \times H' \times 2D_{\text{img}}}$ is formed by concatenating two sets of features (similar to [7]): those from the current image alone (\mathbf{P}^{curr}) and the temporal features from current and prior images (\mathbf{P}^{diff}). In this way, self-attention is mainly required to cope with pose variations and patch comparisons across time in extracting temporal content, removing the need for registration or explicit spatial feature alignment. When no prior scan is available ($\mathbf{x} \in \mathcal{D}_s$), A_{img} is not used and \mathbf{P}^{diff} is replaced by a learnable token $\mathbf{p}^{\text{miss}} \in \mathbb{R}^{D_{\text{img}}}$, replicated across the spatial dimensions. Section 4.5 later demonstrates that A_{img} highlights the value of feature decomposition for tasks such as phrase grounding which require well-localised features [10].

Hereafter, downstream tasks that require solely single image features, \mathbf{P}^{curr} , are referred to as *static tasks*, and the ones that benefit from additional progression information, \mathbf{P}^{diff} , as *temporal tasks*, e.g., report decoding.

3.2. Text-supervision for spatio-temporal learning

Let $\mathbf{w} = (w_1, \dots, w_M)$ denote a vector of M tokens of a report \mathbf{x}_{txt} after tokenisation. We first obtain contextualised token features $E_{\text{txt}}(\mathbf{w}) \in \mathbb{R}^{M \times D_{\text{txt}}}$ by passing a sequence of text tokens $\mathbf{w} = (w_1, \dots, w_M)$ through a BERT encoder E_{txt} [20]. The input sequence is prepended with either a [CLS] or [MLM] token associated with a downstream training objective, conditioning the output features

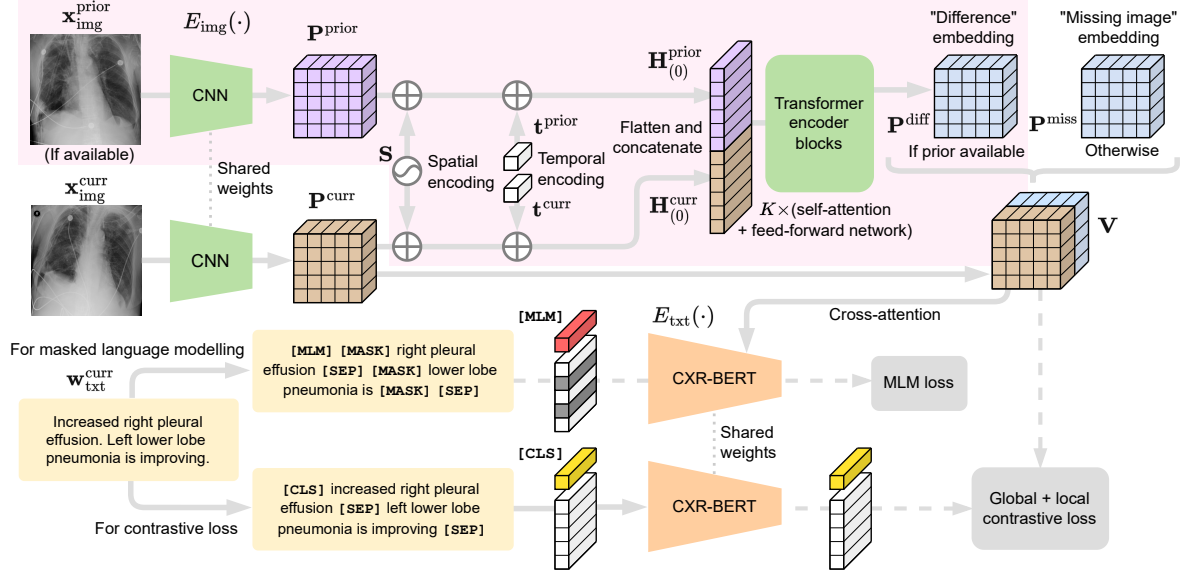


Figure 2. The proposed self-supervised VLP training framework BioViL-T: Image representations \mathbf{V} are extracted from single and multiple input scans (whenever available) using a hybrid CNN and transformer encoder [24, 51]. This design choice is to increase the data-efficiency and enable the fusion of temporal content without requiring image registration. They are later matched with their corresponding text representations obtained with CXR-BERT [9] using local [32] and global InfoNCE [49] training objectives. As an additional model supervision, multi-modal fused representations, obtained with cross-attention, are used for image-guided masked language modelling.

similar to [39, 42]. During training, we do two forward passes through E_{txt} : once with masking at 45% probability (for the MLM objective) and once without masking for contrastive learning, as shown in Figure 2. The text encoder is initialised with the weights of CXR-BERT³ [9] canonical model, trained on domain-specific vocabulary and corpora.

Both text and image features are later projected into a joint latent space with $\phi_{\text{txt}}: \mathbb{R}^{D_{\text{txt}}} \rightarrow \mathbb{R}^D$, and similarly $\mathbf{v}_{w,h}^{\text{proj}} := \phi_{\text{img}}(\mathbf{v}_{w,h})$ where $\phi_{\text{img}}: \mathbb{R}^{D_{\text{img}}} \rightarrow \mathbb{R}^D$, with ϕ being a two-layer perceptron in our experiments.

Contrastive objectives Let $\mathbf{r} := [E_{\text{txt}}(\mathbf{w})]_{[\text{CLS}]}$ denote the global representation of \mathbf{w} , with $\mathbf{r}^{\text{proj}} := \phi_{\text{txt}}(\mathbf{r})$ its projected version. Given projected patch embeddings $\mathbf{v}_{w,h}^{\text{proj}}$, we can compute a global cosine similarity $S_C(\bar{\mathbf{v}}^{\text{proj}}, \mathbf{r}^{\text{proj}})$ and a local similarity using weighted pairwise cosine similarities across text tokens and projected patch embeddings [32, 76]. These similarities are used in both global and local contrastive objectives with the InfoNCE loss [49, 53]. The local loss proves crucial both for static phrase-grounding and temporal image classification (see Table 7), highlighting the importance of localised self-supervision.

Image-guided masked language modelling Prior work [9, 46] has shown that biomedical visual-language learning benefits from an auxiliary task such as MLM since capturing the joint distribution of tokens can stabilise and improve

language understanding during joint learning. Given a batch \mathcal{B} of token vectors \mathbf{w} , it is often defined as the cross-entropy for predicting the randomly sampled masked tokens, $m \in \{1, \dots, M\}$, $\mathcal{L}_{\text{MLM}} = -\frac{1}{|\mathcal{B}|} \sum_{\mathbf{w} \in \mathcal{B}} \log p_{\theta}(\mathbf{w}_m | \mathbf{w}_{\setminus m})$, where θ are the weights of the text encoder E_{txt} .

In the absence of image information, however, certain masked findings and attributes are not readily predicted, e.g., “[MASK] is worsening”. As shown in the general domain [13], visual information can help disambiguate such masked predictions and provide additional cross-modal supervision. Thus, we use cross-attention [22, 66] to the image features $\mathbf{v}_{w,h}^{\text{proj}}$ during this task. Specifically, for our image-guided MLM objective we model $p_{\theta}(\mathbf{w}_m | \mathbf{w}_{\setminus m}, \mathbf{v}_{w,h}^{\text{proj}})$.

3.3. Adaptations to downstream tasks

BioViL-T can be adapted to various downstream tasks. For phrase-grounding and zero-shot inference, we rely on $S_C(\mathbf{r}^{\text{proj}}, \mathbf{v}_{w,h}^{\text{proj}})$ similar to [9, 32]. For multiple-text prompts, projected text embeddings are marginalised prior to ℓ_2 -normalisation [53]. To enable language decoding, $\mathbf{v}_{w,h}^{\text{proj}}$ inputs are cross-attended by text queries \mathbf{w} , and causal-attention is utilised between text tokens [39, 66]. Differing from [9, 32, 81], we show that report generation tasks can greatly benefit from temporal joint latent space.

Conditioning on prior reports In contrast to existing work, we incorporate the prior report as a prompt to contextualise the report generation task: $p_{\Phi}(\mathbf{w}_{\text{txt}}^{\text{curr}} | \mathbf{w}_{\text{txt}}^{\text{prior}}, \mathbf{v}_{w,h}^{\text{proj}})$,

³<https://huggingface.co/microsoft/BiomedVLP-CXR-BERT-general>

where Φ are the multi-modal encoder-decoder network’s weights, and $\mathbf{w}_{\text{txt}}^{\text{curr}}$, $\mathbf{w}_{\text{txt}}^{\text{prior}}$ denote text tokens for current and prior reports respectively. This is analogous to fine-tuning GPT-3 [11] with prompts and instructions [71], but conditioning on both images and the previous report. A dedicated separation token [SEP] is added into the input sequence $[\mathbf{w}_{\text{txt}}^{\text{prior}}, [\text{SEP}], \mathbf{w}_{\text{txt}}^{\text{curr}}]$.

Curation of imaging datasets CXR datasets [36] often contain multiple image acquisitions $\mathcal{Z} = \{\mathbf{x}_1^{\text{img}}, \dots, \mathbf{x}_Z^{\text{img}}\}$ in a single visit due to data quality issues such as a limited field-of-view or scanning the wrong body part (Figure A.4). Unlike [9, 32, 81], we conduct curation to choose higher quality images among the potential candidates instead of performing a random selection. For this step, a separate BioViL-T is trained on ‘clean’ studies with single acquisitions and later used in a zero-shot setting to detect out-of-distribution samples [26, 27] arising from the re-imaging process. The candidate \hat{z} is selected as follows: $\hat{z} = \arg \max_{z \in \mathcal{Z}} S_C(\bar{\mathbf{v}}_z^{\text{proj}}, \mathbf{r}^{\text{proj}})$ s.t. $|s_{\hat{z}} - s_{\mathcal{Z} \setminus \hat{z}}| > \delta$ for a margin δ . This approach is applied to enhance the quality of the temporal classification dataset given its limited size.

4. Datasets & experiments

Here, we demonstrate BioViL-T’s data efficiency and adaptability to a wide range of applications, and show how the model achieves SOTA performance on various downstream tasks by learning from data instances linked across time, making effective use of domain priors and the available training data. Specifically, our model is evaluated on a diverse set of downstream tasks including zero- and few-shot static and temporal image classification, report generation, phrase-grounding [10], and sentence similarity.

MS-CXR-T benchmark We release a new multi-modal benchmark dataset⁴, *MS-CXR-T*, to evaluate chest X-ray VLP models on two distinct temporal tasks: image classification and sentence similarity. The former comprises multi-image and ground-truth label pairs ($N = 1326$) across 5 findings, with classes corresponding to 3 states of disease progression for each finding: {Improving, Stable, Worsening}. The latter quantifies the temporal-semantic similarity of text embeddings extracted from pairs of sentences ($N = 361$). The pairs can be either paraphrases or contradictions in terms of disease progression. The data for both tasks was manually annotated and reviewed by a board certified radiologist. Appendix C provides further details on its data distribution and annotation protocol.

Datasets For pre-training, we use the MIMIC-CXR v2 [28, 36] chest X-ray dataset, which contains longitudinal imaging studies with corresponding radiological reports,

⁴*MS-CXR-T* benchmark dataset can be accessed through PhysioNet: <https://aka.ms/ms-cxr-t>

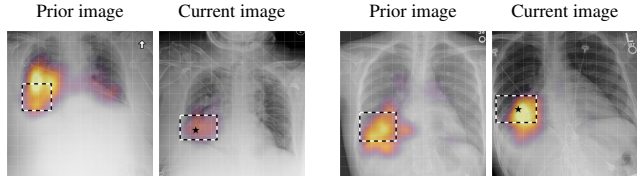


Figure 3. Attention rollout maps [1] from the reference patch (marked with \star) to the current and prior images. The bounding boxes, annotated by a radiologist, show the extent of consolidation. Note that the reference patch attends to its anatomical neighbourhood in the prior image despite the misalignment between prior and current images. The grid (14×14) represents the patch tokens processed in the transformer encoder blocks.

see Fig. B.1 for the distribution of studies. We only use frontal view scans and discard samples where reports do not contain an IMPRESSION section. From this data, we gather 174.1k and 4.9k text-image pairs for training and validation respectively, with a majority of pairs including a prior image: $|\mathcal{D}_m^{\text{train}}| = 118.8k$, $|\mathcal{D}_s^{\text{train}}| = 55.3k$. The text consists of the IMPRESSION section and, for MLM additionally the FINDINGS section if available. Note that *no manual labels* are used during pre-training and *no additional data* is used for the methods that leverage the link between current and prior images. For early stopping we track the validation loss, see Appendix E for implementation details.

Downstream evaluations are performed on a disjoint held-out test set shared across all tasks, $|\mathcal{D}^{\text{test}}| = 2971$. For report generation, we extend this test set with samples from healthy subjects ($N = 815$) to match the prevalence of pathological studies used in prior work [14, 25, 45]. For fine-tuning on temporal image classification, we use labels from the Chest ImaGenome dataset [72] as in [37] (statistics in Table F.2). In detail, we use the following benchmark datasets: (I) *MS-CXR* [10] for phrase grounding, (II) the RSNA Pneumonia dataset [60, 70] to test zero-shot and fine-tuned classification, (III) *MS-CXR-T* for temporal sentence similarity and temporal image classification.

Comparison approaches We compare our approach to other domain-specific SOTA pre-training frameworks [9, 32] specifically on phrase-grounding and zero-shot predictive performance. The non-temporal BioViL framework [9] is most similar to our approach and provides insight into non-temporal pre-training. We additionally compare to internal ablations such as removing the past report during report generation and masking prior images during phrase grounding. For SOTA performance comparison, various AR and nearest-neighbour (NN) based language decoding approaches are used as baselines: IFCC [45], R2Gen [14], CXR-RePaiR-2 [25], and CXR-RePaiR-Select [25].

For the temporal classification task, we compare against a baseline exploiting the BioViL image encoder [9], and an

Table 1. Results for report generation task: Predictions are evaluated in terms of lexical (BLEU-4, ROUGE) and factuality metrics (CHEXBERT, TEM). Approaches are grouped into two broad categories: nearest-neighbour (NN) and auto-regressive (AR). BioViL-T pre-training consistently yields improved decoding. Further, the consistent performance gains of using prior image and report demonstrate the importance of such domain priors. ‘PI / PR’ indicate usage of prior image and report, respectively.

Method	Pre-training	PI / PR	BLEU-4	ROUGE	CHEXBERT	TEM	
Z&F	CXR-RePaiR-2 [25]	BioViL	X / X	2.1	14.3	28.1	12.5
	Baseline (NN) [9]	BioViL	X / X	3.7	20.0	28.3	11.1
	Proposed (NN)	BioViL-T	✓ / X	4.5	20.5	29.0	13.0
AR	Baseline (AR) [9]	BioViL	X / X	7.5 ± 0.1	27.9 ± 0.1	29.3 ± 0.3	13.8 ± 0.1
	Proposed	BioViL-T	✓ / X	8.2 ± 0.1	28.7 ± 0.1	30.2 ± 0.7	16.0 ± 0.3
	Proposed	BioViL-T	✓ / ✓	9.2 ± 0.3	29.6 ± 0.1	31.7 ± 1.0	17.5 ± 0.1

Table 2. Temporal image classification results (repeated for 4 random seeds) on the *MS-CXR-T* benchmark for fully-supervised and zero-/few-shot (Z&F) learning settings, in terms of macro-accuracy across the three classes for each finding. Affine registration is performed for the baseline method (denoted with suffix ‘w/reg’), to partially address the pose variations across scans.

Method (% of labels)	Pre-train	Consolidation	Pl. effusion	Pneumonia	Pneumothorax	Edema	
Z&F	BioViL-T prompt (0%)	Temporal	53.6 ± 1.9	59.7 ± 2.1	58.0 ± 3.9	34.9 ± 1.0	64.2 ± 1.5
	BioViL-T (10%)	Temporal	59.7 ± 2.4	62.4 ± 1.4	60.1 ± 2.1	35.3 ± 2.6	62.6 ± 1.7
SUPERVISED	CNN + Transformer	ImageNet	44.0 ± 2.0	61.3 ± 1.6	45.1 ± 3.5	31.5 ± 3.1	65.5 ± 1.1
	CheXRelNet [37]	ImageNet	47	47	47	36	49
	BioViL [9]	Static	56.1 ± 1.5	62.3 ± 1.1	59.4 ± 1.0	41.7 ± 2.8	67.5 ± 0.8
	BioViL w/reg [9]	Static	56.0 ± 1.5	63.0 ± 0.9	60.2 ± 0.7	42.5 ± 2.7	67.5 ± 0.9
	BioViL-T w/out curation	Temporal	58.9 ± 1.7	65.5 ± 0.7	61.5 ± 2.2	44.4 ± 2.1	67.4 ± 0.8
	BioViL-T	Temporal	61.1 ± 2.4	67.0 ± 0.8	61.9 ± 1.9	42.6 ± 1.6	68.5 ± 0.8

approach that makes use of graph convolutions across regions of interest extracted from bounding boxes [37]. For BioViL, we perform affine image registration (with 4 DoF) for each pair of scans to cope with pose variations, and the encoded images are concatenated along the feature dimension and classified via a multilayer perceptron. For [37], we compare to the three-class setting. Lastly, we benchmark our final text model in isolation against domain specific SOTA models in a temporal sentence similarity task: CXR-BERT [9] and PubMedBert [29].

Metrics Due to class imbalance, we report macro-accuracy for temporal image classification. For phrase grounding, we use mean Intersection-Over-Union (mIoU) and Contrast-to-Noise-Ratio (CNR) [9]. The latter measures the discrepancies between cosine similarities inside and out of the bounding box region without requiring hard thresholds. To evaluate the quality of generated reports, we use both the standard lexical metrics, e.g., BLEU [50], ROUGE-L [41], and also domain-specific factuality metric: CheXbert⁵ [62]. To directly probe the generation of change-related information, we introduce a new metric called temporal entity matching (TEM) to compute the match score of a fixed set of temporal entities (see Appendix D).

⁵The average of the weighted- F_1 score across 14 pathological observations labelled by CheXbert.

Table 3. Report generation results using the same train/test splits from [25], measured by lexical (BLEU-2) and factuality (CHEXBERT) metrics. Baseline results were also collected from [25]. Note the CHEXBERT score covers all 14 observations.

Method	Decoded sections	BLEU-2	CHEXBERT
R2gen [14]	Findings & Impression	21.20 ± 0.10	14.80 ± 0.30
IFCC [45]	Findings	21.70 ± 0.10	27.00 ± 0.40
CXR-RePaiR-Sel [25]	Impression	5.00 ± 0.10	27.40 ± 0.30
BioViL-T	Impression	15.86 ± 0.14	34.83 ± 0.73
BioViL-T	Findings & Impression	21.31 ± 0.19	35.86 ± 0.35

4.1. Temporal pre-training yields data efficiency

Downstream tasks are enabled with minimal labels.

The sections ‘NN’ and ‘Z&F’ on Tables 1 and 2 report zero- and few-shot performance on tasks benefitting from temporal information: temporal image classification and report generation. Here we measure the quality of the learnt joint latent space and the extent to which BioViL-T enables efficient use of raw data. For zero-shot classification we prompt the AR fine-tuned model with prefix: “[FINDING] is” and compare the next-token probability of words meaning ‘improving’, ‘stable’, and ‘worsening’ (Appendix F.4).

Without using any labelled data, Table 2 shows that the proposed AR-based approach already yields performance superior to prior fully-supervised work [37] on temporal image classification. With only 10% of labels, classification fine-tuning provides a further boost, indicating that BioViL-T produces a multi-image encoder readily adapted to temporal tasks. Similarly, in a zero-shot report-retrieval setting, the findings show that compared to temporally-agnostic pre-training, BioViL-T leveraging prior images improves across all metrics. Consistent with prior work [25], the retrieved reports already preserve factuality with high CheXbert scores, more-so than the other metrics which measure fine-grained specifics of phrasing. This demonstrates that the latent space captures the high-level semantics of the clinical features. Fine-grained phrasing however will be substantially improved by AR fine-tuning.

4.2. Achieving SOTA performance with BioViL-T

A wide range of downstream tasks benefit substantially from temporally-aware pre-training.

Through downstream adaptations and fine-tuning our model, we report SOTA performance on report generation and temporal image classification tasks. For the former, using both prior images *and* reports during fine-tuning substantially improves across metrics (Table 1). In particular, TEM metric results show that temporal context is key for accurately describing change in the generated report while avoiding hallucinations (see Table A.1 for examples). Comparing to published results on a comparable test split and

Table 4. Image classification results on RSNA Pneumonia Detection Benchmark [60] for train and test splits of 70% – 30% respectively.

Method	% of Labels	Supervision	Acc.	F1	AUROC
GLoRIA [32]	✗	Zero-shot	0.70	0.58	-
BioViL [9]	✗	Zero-shot	0.732	0.665	0.831
BioViL-T	✗	Zero-shot	0.805	0.706	0.871
BioViL [9]	1%	Few-shot	0.805	0.723	0.881
BioViL-T	1%	Few-shot	0.814	0.730	0.890

metrics (Sec. 4.1), we conclude that BioViL-T with fine-tuning achieves SOTA on report generation, producing reports that are lexically on par with prior work but substantially more factually accurate. Note that we do ‘vanilla’ AR fine-tuning to focus on the impact of the pre-trained encoders, so application-specific supervision [45] could be used in conjunction to further boost performance.

In temporal image classification (Tab. 2), BioViL-T pre-training outperforms the non-temporal baseline (BioViL) and improves on previously-reported results [37] by up to 20 percentage points (pp). Furthermore, baseline methods that rely on image registration (BioViL w/reg), underperform compared to the proposed approach. Further analysis reveals that errors tend to be in cases with disagreement between radiologists (Appendix A.2). We also note that pre-training is critical for a hybrid CNN-transformer model on this task, likely due to the small labelled dataset. Lastly, curation of temporal training data is observed to improve the classification results by .68 pp aggregated across the findings, see Appendix A.4 for details.

4.3. Static tasks benefit from temporal learning

BioViL-T broadens the range of applicable downstream tasks whilst contributing to performance on static tasks.

In this section, we demonstrate that performance improvements afforded by BioViL-T are not restricted to temporal tasks – static tasks also benefit. Table 4 reports results on zero- and few-shot pneumonia classification from single images [60], where BioViL-T establishes a new SOTA compared to prior work [9, 32].

We see a similar trend on the MS-CXR phrase grounding benchmark (Tab. 5). This task can be solved with single images, however we show that the inclusion of the prior image (where available) does not impair the performance of BioViL-T. Feature decomposition effectively preserves localised information from the current image.

4.4. Towards better sentence embedding quality

Language models acquire increased temporal sensitivity.

We hypothesise that text encoders learn temporal semantics through supervision from longitudinal image series. To verify this, RadNLI [45] and MS-CXR-T datasets are used in a zero-shot binary classification setting. Cosine similarity

Table 5. Results on MS-CXR benchmark [10] (5-runs with different seeds), “Multi-image” column indicates the input images used at test time.

Method	Multi-Image	Avg. CNR	Avg. mIoU
BioViL [9]	✗	1.07 ± 0.04	0.229 ± 0.005
+ Local loss [9, 32]	✗	1.21 ± 0.05	0.202 ± 0.010
BioViL-T	✗	1.33 ± 0.04	0.243 ± 0.005
BioViL-T	✓	1.32 ± 0.04	0.240 ± 0.005

Table 6. Results on MS-CXR-T sentence similarity benchmark.

Text Model	MS-CXR-T (361 pairs)		RadNLI (145 pairs)	
	Accuracy	ROC-AUC	Accuracy	ROC-AUC
PubMedBERT [29]	60.39	.542	81.38	.727
CXR-BERT-G [9]	62.60	.601	87.59	.902
CXR-BERT-S [9]	78.12	.837	89.66	.932
BioViL-T	87.77 ± 0.5	.933 ± .003	90.52 ± 1.0	.947 ± .003

of sentence pair embeddings [56] are treated as class-logits to label each pair either as paraphrase or contradiction. See Appendix F.6 for further details.

Our text model is benchmarked against SOTA domain-specific BERT models. Table 6 shows that the proposed framework greatly increases the sensitivity of sentence embeddings to temporal content whilst better capturing the static content (RadNLI). Note that CXR-BERT-Specialised [9] is learnt through single-images starting from the same canonical model, illustrating the substantial increase in temporal and static sensitivity due to BioViL-T pre-training.

4.5. Ablation experiments

In Table 7 we report extensive ablations across the multi-image encoder architecture, pre-training choices, and AR fine-tuning for report generation.

Image encoder Table 7 shows that decomposition of static and progression features is essential to ensure good performance on single-image tasks, such as phrase grounding. For temporal representations, on the other hand, positional encodings (T) are essential to disambiguate the order of scans, i.e., permutation variance across time.

Model pre-training The corresponding results are shown in the middle section of Table 7. The local contrastive loss proves crucial to ensure meaningful language supervision during pre-training, followed by the image-guided MLM objective. Lastly, use of the FINDINGS section results in only minor performance gains as the key findings are already captured in the IMPRESSION section.

Report generation The importance of prior image and report is demonstrated by the substantial drop in the “no prior image and report” ablation, confirming our hypothesis that temporal context is crucial for improving report quality. While both inputs are crucial for optimal performance,

Table 7. Ablation study on image encoder, pre-training settings, and report generation (one component at a time, and repeated for 4 random seeds). Note that for temporal classification, linear probing is applied to frozen image embeddings. In report generation, the baseline method is fine-tuned with both prior image and report.

	Ablation	Avg. CNR (mIoU)	Pl. Effusion Acc.
Encoder	Baseline	1.33 ± 0.02 (.248)	64.8 ± 0.6
	- Temporal pos. encoding	1.32 ± 0.02 (.242)	62.9 ± 1.0
	- Feature decomposition	1.11 ± 0.08 (.203)	64.0 ± 0.6
Pre-training	Baseline	1.33 ± 0.02 (.248)	64.8 ± 0.6
	- Use of findings section	1.32 ± 0.01 (.246)	63.8 ± 0.8
	- MLM loss	1.28 ± 0.02 (.238)	63.2 ± 0.7
	- Local contrastive loss	1.18 ± 0.02 (.236)	60.2 ± 0.6
	Ablation	ROUGE	TEM
Report gen.	Baseline	29.64 ± 0.08	17.54 ± 0.11
	- Prior image	29.35 ± 0.25	16.30 ± 0.40
	- Prior report	28.67 ± 0.12	16.00 ± 0.30
	- (Prior image and report)	27.78 ± 0.09	13.65 ± 0.48
	- Separation token	26.00 ± 0.40	15.50 ± 1.06

the prior report is more so because it summarises the image and provides a clearer signal. The prior image however cannot be dismissed entirely as it provides granular details which may not always be documented in a report. Finally, we found the separation token is crucial in differentiating between the predicted tokens for the current report and tokens from the prior report.

4.6. Which tokens require a prior image in MLM?

We leverage the MLM objective in an inference setting to analyse the influence of prior images in predicting masked tokens. Inspired by the Δ image loss of [8], we define Δ_{img}^{prior} as the change in loss by conditioning the estimation with a prior image for a given token w as follows:

$$\Delta_{img}^{prior}(w) = l(w, \mathbf{x}_{img}^{curr}, \emptyset) - l(w, \mathbf{x}_{img}^{curr}, \mathbf{x}_{img}^{prior}) \quad (2)$$

where $l(w, \mathbf{x}_{img}^{curr}, \mathbf{x}_{img}^{prior})$ is the cross-entropy of predicting the masked token w given visual features (MLM loss for a single token), averaged over sentences in which w appears. Δ_{img}^{prior} is a measure of how much that token benefits from access to the prior image, as well as an assessment of the contribution of the prior image to the image representation. In Figure 4 we show the distribution of Δ_{img}^{prior} as a function of token category (e.g., *Anatomy*, *Positional*; see F.5 for annotation details). For *Progression*-type terms in particular, the model heavily relies on the prior image for image-guided MLM. We further observe that this effect is specific to temporal tokens; as expected, those from other semantic categories do not consistently rely on the prior image.

5. Conclusion

In this paper, we introduced BioViL-T, a vision-language pre-training framework enabling alignment between text and multiple images. BioViL-T makes use of

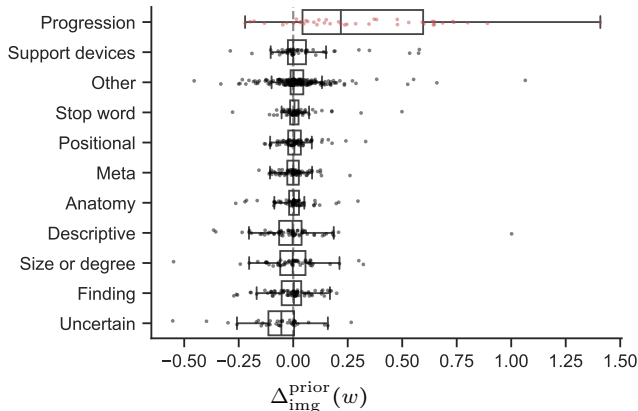


Figure 4. Mean token-level increase in image-guided MLM loss when prior image is discarded, grouped by token category. The prior image is excluded during inference to measure its impact on masked token predictions. *Progression* tokens are significantly better predicted when prior images are incorporated into image embeddings. The top five *Progression* tokens are ‘persist’, ‘improving’, ‘remains’, ‘unchanged’, and ‘residual’.

a novel multi-image encoder and explicitly decomposes static-temporal features to augment the current image representation with information from prior images. This enables the grounding of temporal references in the text. To our knowledge, this is the first method capable of leveraging the temporal content commonly present in biomedical text. It addresses an important limitation in existing VLP approaches, which simply discard such context. Also, incorporating such multi-modal temporal content provides strong learning signals to the model, resulting in richer representations and improved downstream performance.

We demonstrate the value of this paradigm through extensive experiments: BioViL-T excels on both static and temporal tasks, establishing new SOTA on report generation, temporal image classification, few/zero-shot pneumonia detection, and phrase grounding. Furthermore, we release a new multi-modal benchmark (*MS-CXR-T*) to measure the quality of image and text representations in terms of temporal semantics, enabling more diverse evaluation of biomedical VLP models. The corresponding model weights⁶ and code⁷ are publicly available.

Further exploration and evaluation are required on diverse datasets to characterise what kinds of tasks would benefit from a temporal modelling approach, and specifically from the proposed methodology.

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⁶Models can be found at: <https://aka.ms/biovil-t-model>

⁷Code can be found at: <https://aka.ms/biovil-t-code>

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