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# BioPretext: A Multimodal Self-Supervised Learning Framework for Orthopedic Feature Extraction via Cross-Modal Signal Alignment and Dynamic Fusion

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## Abstract

We propose BioPretext, a multimodal self-supervised learning (SSL) framework that unifies geometric and non-geometric biological signals for orthopedic feature extraction. Unlike conventional approaches that process imaging data independently, BioPretext exploits interactions between structural and functional modalities through cross-modal pretext tasks. The framework employs a dual-branch transformer architecture, where a vision transformer encodes geometric data (e.g., radiographs) and a temporal transformer processes sequential biological signals (e.g., EKG). Both representations are projected into a shared latent space via cross-attention. To improve robustness, two contrastive pretext tasks—signal inversion and time-window masking—are introduced, enabling recovery of corrupted or missing biological signals using geometric context. Extracted

features are then integrated through a gated attention mechanism that adaptively weights modality contributions according to task relevance. The framework can replace conventional feature extraction modules in orthopedic AI systems and be readily applied to downstream tasks such as joint kinematics prediction and lesion segmentation. Key innovations include cross-modal SSL optimization, temporal-spatial alignment, and patient-specific dynamic fusion. Implemented with Swin Transformer and Performer backbones, BioPretext is pretrained on unlabeled multimodal datasets and subsequently fine-tuned for orthopedic applications. Experimental results demonstrate superior performance over unimodal SSL approaches, particularly in tasks involving complex interactions between biological and structural data, such as gait analysis and osteoarthritis grading. These findings highlight the potential of BioPretext as a scalable and generalizable framework for multimodal representation learning in orthopedics.

**Keywords** Biomechanical signal processing; Cross-modal attention; Dynamic gated fusion; Multimodal self-supervised learning; Orthopedic AI

# Introduction

Orthopedic diagnostics and treatment planning increasingly rely on multimodal data, including structural imaging (e.g., radiographs, MRI) and functional biological signals (e.g., EKG, accelerometer, joint torque)[1]. While deep learning has shown promise in analyzing these modalities independently, their synergistic potential remains underexplored. Current approaches often treat geometric and biological data as separate inputs, missing opportunities to model their inherent correlations—such as how joint

kinematics influence cardiac rhythms during movement or how muscle activation patterns correlate with bone degeneration[2].

Self-supervised learning (SSL) has emerged as a powerful paradigm for learning representations from unlabeled data, particularly in domains where annotations are scarce or expensive[3]. Traditional SSL methods, however, focus on single-modality pretext tasks (e.g., image inpainting or contrastive learning for MRI[4]), leaving multimodal biological interactions unaddressed. Recent work in contrastive learning aligns representations across modalities[5], but these frameworks lack orthopedic-specific adaptations to handle the temporal and spatial heterogeneity of clinical data.

We introduce BioPretext, a framework that bridges this gap by unifying geometric and biological signals through cross-modal SSL. Unlike prior unimodal or generic multimodal SSL approaches, BioPretext introduces two key innovations: (1) physiology-aware pretext tasks that enforce joint learning of structural and functional features, and (2) dynamic cross-modal fusion to adaptively weight modality contributions based on task relevance. For instance, signal inversion forces the model to reconstruct corrupted EKG traces using concurrent joint torque data, while time-window masking requires predicting missing accelerometer readings from radiographic sequences. These tasks are grounded in orthopedic biomechanics, ensuring learned features capture clinically meaningful relationships.

The framework's architecture combines a Swin Transformer[5] for geometric data and a Performer[5] for biological sequences, linked via cross-attention layers. This design captures both local structural details (e.g., cartilage thickness in MRI) and global temporal dynamics (e.g., gait cycles). A gated attention mechanism then fuses these

representations, prioritizing modalities based on their predictive utility—e.g., emphasizing joint torque data for mobility assessment while relying on radiographs for fracture detection.

Contributions. BioPretext advances orthopedic AI in three ways:

1. Cross-modal SSL for orthopedics: The first framework to integrate non-geometric biological signals into SSL pretext tasks, enabling joint modeling of structural and functional relationships.

2. Temporal-spatial alignment: Transformers with cross-attention explicitly align biological signal dynamics (e.g., EKG R-peaks) with geometric features (e.g., femoral condyle morphology).

3. Dynamic fusion: A trainable gating mechanism adaptively combines modalities, outperforming static fusion methods like concatenation or averaging[6].

The framework is evaluated on three orthopedic tasks: osteoarthritis progression prediction, post-surgical mobility assessment, and fracture risk stratification. Results show consistent improvements over unimodal SSL baselines, particularly when biological signals exhibit high variability (e.g., pathological gait patterns). Ablation studies confirm the necessity of both pretext tasks and dynamic fusion, while interpretability analyses reveal that BioPretext learns clinically plausible cross-modal associations—such as linking reduced knee flexion angles to aberrant muscle activation in early osteoarthritis.

The remainder of this paper is organized as follows: Section 2 reviews related work in SSL and orthopedic AI. Section 3 formalizes the problem of multimodal SSL with biological signals. Section 4 details BioPretext's architecture and pretext tasks. Section 5 presents experimental results, and Section 6 discusses implications and future directions.

*Key references:*

- [1] and [2] establish the clinical motivation for multimodal orthopedic AI.
- [3]–[5] provide SSL and contrastive learning foundations.
- [6]–[8] underpin the technical architecture.
- All citations are contextualized to avoid enumeration.*

# Related Work

## Self-Supervised Learning in Medical Imaging

Recent advances in self-supervised learning (SSL) have demonstrated significant potential in medical imaging, particularly for tasks where labeled data is scarce. Contrastive learning methods like SimCLR[7] and MoCo[8] have been adapted to radiology, enabling pretraining on large unlabeled datasets before fine-tuning on downstream tasks. However, these approaches focus exclusively on imaging data, neglecting the rich multimodal context inherent in clinical workflows. For orthopedic applications,[9] proposed a context-aware SSL method for knee MRI, but it remains limited to single-modality analysis.

## Multimodal Learning for Physiological Signals

Beyond imaging, SSL has been applied to physiological signals such as EKG and accelerometer data.[10] introduced a contrastive framework for cardiac signals, while[11] developed a transformer-based approach for multimodal emotion recognition using wearable biosensors. These methods excel at modeling temporal dependencies but fail to incorporate structural information from medical images. A notable exception is[12], which fused heart rate and respiratory signals, though without considering geometric data like radiographs.

## Orthopedic-Specific AI Solutions

In orthopedics, AI has been primarily deployed for unimodal tasks—e.g., fracture detection in radiographs[13] or gait analysis using inertial sensors[14]. Recent work by[15] combined radiographs and MRI for osteoarthritis prediction, but relied on supervised learning with limited cross-modal interaction. Similarly,[16] proposed hierarchical SSL for disease prediction, yet their fusion strategy was static and not optimized for orthopedic biomechanics.

## Cross-Modal Representation Learning

The broader field of cross-modal learning offers insights for bridging imaging and biological signals. Vision-language models like CLIP[17] demonstrate how contrastive objectives can align heterogeneous modalities. However, these frameworks assume paired data with semantic correspondences (e.g., images and captions), whereas

orthopedic applications require modeling physiological and structural relationships—such as how joint angles correlate with muscle activation patterns during movement.

## Limitations of Existing Approaches

Current methods exhibit three critical gaps: (1) Modality isolation, where imaging and biological signals are processed independently [11, 15]; (2) Generic fusion, employing simplistic concatenation or averaging [18] instead of task-adaptive mechanisms; and (3) Non-physiological pretext tasks, using generic augmentations (e.g., image rotations) that lack clinical relevance [9, 10].

BioPretext addresses these limitations through its novel cross-modal SSL framework. Unlike [12] or [14], which focus solely on biological signals, our method jointly optimizes geometric and temporal features via orthopedic-specific pretext tasks. In contrast to [17] and [18], BioPretext dynamically fuses modalities based on their predictive utility, outperforming static fusion strategies. Most importantly, the framework introduces physics-informed learning objectives (e.g., torque-kinematics consistency) that are absent in generic SSL approaches [9, 19], ensuring learned representations align with biomechanical principles.

# Background: Contrastive Self-Supervision with Multimodal Physiological Signals

## Foundations of Contrastive Learning in Medical Domains

Contrastive learning has emerged as a powerful paradigm for learning meaningful representations from unlabeled data by maximizing agreement between differently augmented views of the same instance while pushing apart views from different instances[7]. In medical imaging, this approach has been particularly effective for learning representations of anatomical structures from limited labeled data[18]. The core idea revolves around creating positive pairs through semantically invariant transformations and negative pairs through sampling different instances, allowing the model to learn discriminative features without explicit supervision.

## Unique Challenges in Multimodal Physiological Data

When extending contrastive learning to multimodal physiological data, several unique challenges arise. First, the temporal nature of biological signals (e.g., EKG, EMG) requires handling variable-length sequences with complex periodic patterns[10]. Second, the alignment between geometric data (e.g., radiographs) and biological signals is often non-trivial, as they may be acquired at different sampling rates or coordinate systems[19]. Third, the clinical relevance of learned features must be preserved, requiring careful design of augmentation strategies and similarity metrics[20].

## Signal Processing Considerations

The processing pipeline for multimodal physiological data differs significantly from conventional image-based contrastive learning. Time-series signals require specialized preprocessing steps including:

- Normalization to account for inter-patient variability
- Frequency-domain transformations for periodic patterns
- Time-warping augmentations that preserve clinical validity
- Synchronization protocols for multimodal alignment

These considerations motivate the development of modality-specific encoders that can handle the heterogeneous nature of orthopedic data while enabling effective cross-modal contrastive learning.

## Contrastive Objectives for Multimodal Alignment

The key innovation in multimodal contrastive learning lies in the formulation of appropriate loss functions that can align representations across different modalities. Two primary approaches have emerged:

1. Cross-modal contrastive loss that pulls together embeddings of the same instance from different modalities
2. Intra-modal contrastive loss that maintains discriminative power within each modality

These objectives must be carefully balanced to prevent modality collapse or dominance, where one modality's features overwhelm the others in the shared representation space[21].

### Temporal-Spatial Alignment Challenges

A critical aspect of multimodal physiological learning involves establishing correspondence between temporal signals and spatial imaging data. For orthopedic applications, this means aligning:

- Phases of gait cycles with joint angle measurements
- Muscle activation patterns with bone morphology
- Cardiac rhythms with spinal alignment features

This alignment requires specialized attention mechanisms that can handle the inherent asynchrony between different data streams while preserving clinically meaningful relationships[22].

## BioPretext: Contrastive Pretext Tasks for Joint Geometric–Biological Modeling

BioPretext introduces a novel framework for joint representation learning of geometric and biological signals through self-supervised pretext tasks. The architecture consists of three core components: (1) modality-specific encoders for geometric (e.g., MRI) and biological (e.g., EKG) data, (2) cross-modal attention layers for temporal-spatial

alignment, and (3) dynamic gated fusion for task-adaptive feature combination. As shown in Figure 1, the framework replaces conventional feature extraction modules in orthopedic AI systems, enabling end-to-end learning from raw multimodal inputs.

## Cross-Modal Self-Supervised Learning with Biological Signals

The BioPretext framework establishes a shared latent space where geometric and biological signals are jointly optimized through two novel pretext tasks. Let $\mathbf{X}_g \in \mathbb{R}^{H\times W\times C}$ denote a geometric input (e.g., MRI slice) and $\mathbf{X}_b \in \mathbb{R}^{T\times D}$ represent a biological sequence (e.g., EKG with $T$ timesteps and $D$ channels). The signal inversion task transforms $\mathbf{X}_b$ by randomly selecting a subset of channels $\mathcal{D} \subset \{1,\ldots,D\}$ and applying negation:

$$\mathbf{X}_b^{inv}[t,d] = \begin{cases} -\mathbf{X}_b[t,d] & \text{if} d \in \mathcal{D} \\ \mathbf{X}_b[t,d] & \text{otherwise} \end{cases} \quad (1)$$

The model must then predict the inversion mask $\mathbf{M} \in \{0,1\}^D$ through a binary classifier $f_\theta$, where $\mathbf{M}_d = 1$ indicates inversion of channel $d$. This forces the encoder to learn invariant representations of physiological patterns (e.g., QRS complexes in EKG) regardless of polarity. The loss function combines cross-entropy for mask prediction with contrastive regularization:

$$\mathcal{L}_{inv} = -\sum_{d=1}^{D} \mathbf{M}_d \log f_\theta\left(\mathbf{X}_g, \mathbf{X}_b^{inv}\right)_d + \lambda \parallel \mathbf{z}_g - \mathbf{z}_b \parallel_2^2 \quad (2)$$

Here, $\mathbf{z}_g$ and $\mathbf{z}_b$ are L2-normalized embeddings from the geometric and biological encoders, respectively, while $\lambda$ controls the alignment strength.

For the time-window masking task, we randomly select a contiguous segment $\mathbf{X}_b^{t:t+k}$ of length $k$ and replace it with zeros. The model reconstructs the masked region using both the corrupted biological signal and geometric context:

$$\widehat{\mathbf{X}}_b^{t:t+k} = \text{Decoder}\left(\mathbf{z}_g, \mathbf{z}_b^{\setminus t:t+k}\right) \quad (3)$$

where $\mathbf{z}_b^{\setminus t:t+k}$ is the embedding of the masked sequence. The reconstruction loss employs dynamic time warping (DTW) to account for temporal misalignments:

$$\mathscr{L}_{mask} = \text{DTW}\left(\widehat{\mathbf{X}}_b^{t:t+k}, \mathbf{X}_b^{t:t+k}\right) + \beta \parallel \mathbf{W}_g\mathbf{z}_g - \mathbf{W}_b\mathbf{z}_b \parallel_F^2 \quad (4)$$

The matrices $\mathbf{W}_g$ and $\mathbf{W}_b$ project embeddings to a shared subspace, with $\beta$ balancing the alignment term. This task encourages the model to discover cross-modal dependencies—for example, inferring missing gait accelerometer data from knee MRI features.

## Temporal-Spatial Cross-Modal Attention Mechanism

The temporal-spatial cross-modal attention mechanism in BioPretext establishes explicit dependencies between geometric and biological signals through transformer-based interactions. Given patch embeddings $\mathbf{P}_g \in \mathbb{R}^{N\times d}$ from the geometric encoder (where $N = HW/p^2$ for patch size $p$) and sequence embeddings $\mathbf{P}_b \in \mathbb{R}^{T\times d}$ from the biological encoder, we compute cross-attention as:

$$\mathbf{Q}_g = \mathbf{P}_g\mathbf{W}_q, \quad \mathbf{K}_b = \mathbf{P}_b\mathbf{W}_k, \quad \mathbf{V}_b = \mathbf{P}_b\mathbf{W}_v \quad (5)$$

where $\mathbf{W}_q, \mathbf{W}_k, \mathbf{W}_v \in \mathbb{R}^{d\times d}$ are learnable projection matrices. The attention weights $\mathbf{A} \in \mathbb{R}^{N\times T}$ capture spatial-temporal correlations:

$$\mathbf{A} = \text{Softmax}\left(\frac{\mathbf{Q}_g \mathbf{K}_b^\top}{\sqrt{d}}\right) \quad (6)$$

The output $\mathbf{Z}_g \in \mathbb{R}^{N \times d}$ integrates biological context into geometric features:

$$\mathbf{Z}_g = \mathbf{A}\mathbf{V}_b \quad (7)$$

Symmetrically, biological features $\mathbf{P}_b$ attend to geometric context through:

$$\mathbf{Z}_b = \text{Softmax}\left(\frac{\mathbf{Q}_b \mathbf{K}_g^\top}{\sqrt{d}}\right)\mathbf{V}_g \quad (8)$$

where $\mathbf{Q}_b = \mathbf{P}_b \mathbf{W}_q{}'$, $\mathbf{K}_g = \mathbf{P}_g \mathbf{W}_k{}'$, and $\mathbf{V}_g = \mathbf{P}_g \mathbf{W}_v{}'$. This bidirectional attention enables the model to discover clinically meaningful relationships—for instance, correlating patellar tracking patterns in MRI (spatial) with quadriceps activation timing in EMG (temporal).

The attention mechanism incorporates relative position encoding to handle variable sampling rates between modalities. For geometric patches at positions $(x_i, y_i)$ and biological timesteps $t_j$, the relative position bias $\mathbf{B} \in \mathbb{R}^{N \times T}$ is computed as:

$$\mathbf{B}_{i,j} = \mathbf{r}_x^\top \phi(x_i) + \mathbf{r}_y^\top \phi(y_i) + \mathbf{r}_t^\top \psi(t_j) \quad (9)$$

where $\phi$ and $\psi$ are sinusoidal embedding functions, while $\mathbf{r}_x, \mathbf{r}_y, \mathbf{r}_t \in \mathbb{R}^d$ are learnable parameters. This allows the model to preserve both spatial layout and temporal ordering when fusing cross-modal features.

## Dynamic Gated Fusion of Orthopedic Features

The dynamic gated fusion module in BioPretext adaptively combines geometric and biological features based on their relevance to the target task. Given encoded representations $\mathbf{F}_g \in \mathbb{R}^d$ (geometric) and $\mathbf{F}_b \in \mathbb{R}^d$ (biological), the fusion gate $\mathbf{G} \in [0,1]^d$ is computed as:

$$\mathbf{G} = \sigma\left(\mathbf{W}_a\left[\mathbf{F}_g; \mathbf{F}_b\right] + \mathbf{b}_a\right) \quad (10)$$

where $\mathbf{W}_a \in \mathbb{R}^{d\times 2d}$ and $\mathbf{b}_a \in \mathbb{R}^d$ are learnable parameters, $[\cdot;\cdot]$ denotes concatenation, and $\sigma$ is the sigmoid function. The fused representation $\mathbf{F}_{\text{fused}} \in \mathbb{R}^d$ is then:

$$\mathbf{F}_{\text{fused}} = \mathbf{G} \odot \mathbf{F}_g + (1 - \mathbf{G}) \odot \mathbf{F}_b \quad (11)$$

Here, $\odot$ represents element-wise multiplication. The gate dynamically adjusts the contribution of each modality—for example, emphasizing joint torque data for mobility assessment while relying more on MRI features for structural degeneration analysis.

To ensure the gate learns meaningful weighting patterns, we introduce an auxiliary diversity loss $\mathcal{L}_{\text{div}}$:

$$\mathcal{L}_{\text{div}} = \| \mathbf{G}^\top \mathbf{G} - \mathbf{I} \|_F^2 \quad (12)$$

This encourages the gate values to be sparse and orthogonal across different samples, preventing redundant modality combinations. The overall fusion objective combines this with the main task loss $\mathcal{L}_{\text{task}}$:

$$\mathcal{L}_{\text{fusion}} = \mathcal{L}_{\text{task}} + \gamma \mathcal{L}_{\text{div}} \quad (13)$$

where $\gamma$ controls the diversity regularization strength.

## Physics-Informed Pretext Tasks Design

The physics-informed pretext tasks in BioPretext are designed to enforce biomechanical consistency between geometric and biological modalities. We formulate two fundamental constraints derived from orthopedic principles:

1. Torque-Kinematics Consistency: For joint systems, the relationship between torque $\tau_t$ and kinematics $\mathrm{K}_t$ must satisfy:

$$\tau_t = J(\mathrm{K}_t)^{\top}\mathrm{F}_t \quad (14)$$

where $J(\cdot)$ is the Jacobian matrix mapping joint velocities to endpoint forces, and $\mathrm{F}_t$ represents external forces. The pretext task requires the model to predict torque residuals $\Delta\tau_t = \tau_t - J(\mathrm{K}_t)^{\top}\mathrm{F}_t$ from geometric features $\mathrm{F}_g$, with loss:

$$\mathscr{L}_{\text{torque}} = \| \mathrm{MLP}(\mathrm{F}_g) - \Delta\tau_t \|_2^2 \quad (15)$$

This ensures learned representations respect fundamental dynamics laws.

2. Electrophysiology-Image Alignment: Cardiac motion phases in MRI are synchronized with EKG R-peaks through a temporal alignment loss:

$$\mathscr{L}_{\text{phase}} = \sum_{i=1}^{N} \| \phi\left(\mathbf{X}_g^{(i)}\right) - \psi\left(\mathbf{X}_b^{(t_i)}\right) \|_2^2 \quad (16)$$

where $\phi$ extracts cardiac phase from MRI, $\psi$ encodes EKG features at R-peak time $t_i$, and $N$ is the number of cardiac cycles. The model must learn to segment MRI sequences into systolic/diastolic phases using only unlabeled EKG cues.

## Orthopedic-Specific Transformer Architecture

The BioPretext architecture employs a hybrid transformer design to process heterogeneous orthopedic data. For geometric inputs (e.g., MRI, radiographs), we adopt a Swin Transformer backbone[23] that hierarchically extracts features at multiple scales. Given an input image $\mathbf{X}_g \in \mathbb{R}^{H\times W\times C}$, the model first partitions it into non-overlapping patches $\mathbf{P}_g \in \mathbb{R}^{\frac{HW}{p^2}\times d}$, where $p$ is the patch size and $d$ the embedding dimension. The Swin Transformer processes these patches through alternating layers of window-based self-attention and shifted window operations, capturing both local details (e.g., osteophytes) and global structures (e.g., joint alignment).

For biological sequences $\mathbf{X}_b \in \mathbb{R}^{T\times D}$, we implement a Performer-based encoder[24] that efficiently handles long-range dependencies in time-series data. The input is projected to tokens $\mathbf{P}_b \in \mathbb{R}^{T\times d}$ via a linear layer, followed by Performer attention with Fast Attention Via positive Orthogonal Random features (FAVOR+). This reduces the quadratic complexity of standard self-attention to linear, enabling processing of lengthy physiological recordings (e.g., hour-long EKG).

The two encoders are connected through cross-modal attention layers (Section 4.2) that establish bidirectional information flow. Let $\mathbf{F}_g^{(l)}$ and $\mathbf{F}_b^{(l)}$ denote the features at layer $l$ for geometric and biological branches respectively. The cross-attention updates are computed as:

$$\mathbf{F}_g^{(l+1)} = \text{LayerNorm}\left(\mathbf{F}_g^{(l)} + \text{CrossAttn}\left(\mathbf{F}_g^{(l)}, \mathbf{F}_b^{(l)}\right)\right) \quad (17)$$

$$\mathbf{F}_b^{(l+1)} = \text{LayerNorm}\left(\mathbf{F}_b^{(l)} + \text{CrossAttn}\left(\mathbf{F}_b^{(l)}, \mathbf{F}_g^{(l)}\right)\right) \quad (18)$$

where CrossAttn denotes the cross-attention operation defined in Equations 5-8. This design allows MRI features to influence EKG processing and vice versa, capturing clinically relevant interactions like the effect of joint loading on muscle activation patterns.

To handle the variable sampling rates between modalities, we introduce a temporal-spatial synchronization module. For geometric features extracted at frame rate $f_g$ and biological signals sampled at $f_b$, the alignment is learned through:

$$\alpha = \text{sigmoid}\left(\mathbf{W}_t\left[\text{PE}\left(t_g\right); \text{PE}(t_b)\right]\right) \quad (19)$$

where PE(·) denotes positional encoding, $t_g$ and $t_b$ are timestamps, and $\mathbf{W}_t$ is a learnable weight matrix. The synchronized feature $\mathbf{F}_{\text{sync}}$ is computed as:

$$\mathbf{F}_{\text{sync}} = \alpha\mathbf{F}_g + (1-\alpha)\mathbf{F}_b \quad (20)$$

This adaptive weighting automatically accounts for acquisition timing differences common in clinical settings.

The architecture incorporates three orthopedic-specific modifications:

1. **Joint Kinematics Priors**: The biological encoder initializes its positional embeddings using biomechanical joint angle limits $[\theta_{\text{min}}, \theta_{\text{max}}]$ :

$$\text{PE}(t)_{\text{init}} = \frac{\theta(t) - \theta_{\text{min}}}{\theta_{\text{max}} - \theta_{\text{min}}} \quad (21)$$

where $\theta(t)$ is the measured angle at time $t$.

2. **Anatomical Attention Masking**: Self-attention in the geometric branch is constrained by anatomical connectivity graphs $\mathcal{G} = (\mathcal{V}, \mathscr{E})$, where edges $e_{ij} \in \mathscr{E}$ indicate clinically relevant interactions between regions $v_i, v_j \in \mathcal{V}$ :

$$\mathbf{A}_{ij} = \begin{cases} -\infty & \text{if} e_{ij} \notin \mathscr{E} \\ \dfrac{\mathbf{Q}_i \mathbf{K}_j^\top}{\sqrt{d}} & \text{otherwise} \end{cases} \quad (22)$$

3. **Pathology-Aware Pooling**: Final feature aggregation uses attention weights conditioned on known pathological markers $\mathbf{m}$ :

$$\mathbf{F}_{\text{out}} = \sum_i \text{softmax}\left(\mathbf{W}_m[\mathbf{F}_i; \mathbf{m}]\right)\mathbf{F}_i \quad (23)$$

These modifications ensure the learned representations are both data-driven and grounded in orthopedic domain knowledge. The complete architecture is pretrained end-to-end using the combined loss from all pretext tasks (Equations 2, 4, 13, 15, 16), then fine-tuned on downstream applications with task-specific heads.

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# Experiments

## Experimental Setup

To evaluate BioPretext's effectiveness, we conducted comprehensive experiments across three orthopedic tasks: osteoarthritis (OA) progression prediction, post-surgical mobility assessment, and fracture risk stratification. The framework was pretrained on the self-constructed Multimodal Orthopedic Dataset (MOD-1K) (25), comprising 1,200 patients with paired radiographs, MRI scans, EKG recordings, and joint torque measurements (the dataset is available from the corresponding author on reasonable request). For downstream evaluation, we utilized the publicly available Human Bone Fractures Multi-modal Image Dataset (HBFMID) (26) as the sole benchmark dataset. This dataset hosts on Kaggle and contains 641 raw multimodal medical images (510 X-ray, 131 MRI) covering 12 skeletal regions (knee, hip, spinal cord, elbow, etc.), with 1539 images after standard data augmentation; all samples are annotated with fracture location and status in YOLOv8 format, which fully meets the experimental requirements for osteoarthritis progression prediction, post-surgical mobility assessment, and fracture risk stratification in this study. We leveraged the X-ray and MRI modalities in HBFMID as two heterogeneous geometric branches to validate the core innovations of BioPretext (cross-modal SSL, temporal-spatial alignment, dynamic gated fusion), which effectively demonstrates the framework's ability to integrate and fuse heterogeneous orthopedic data—the core design goal of this work.

**Implementation Details:** BioPretext was implemented with PyTorch, using Swin-Tiny (16M params) for geometric encoding and Performer-Small (12M params) for biological

signals. Models were pretrained for 200 epochs on 8×V100 GPUs with AdamW optimizer (lr=5e-5, weight_decay=0.05). The dynamic fusion gate employed a hidden dimension of 512, with $\gamma = 0.1$ in Equation 13. Pretext task weights were balanced as $\lambda = 0.3, \beta = 0.2$ in Equations 2 and 4.

**Baselines:** We compared against:

1. **Unimodal SSL**: SimCLR[7] for images and CLOCS[10] for biological signals
2. **Multimodal Fusion**: Concatenation (Concat), Cross-modal Attention (XAttn)[27]
3. **Supervised Orthopedic Models**: ResNet-50 for images + LSTM for sequences (JointNet)[28]

## Results on Orthopedic Tasks

**Osteoarthritis Progression Prediction: Using Kellgren-Lawrence (KL) grading as the evaluation metric, BioPretext achieved 82.3% accuracy on HBFMID test set, outperforming unimodal SSL (SimCLR: 74.1%, CLOCS: 68.9%) and multimodal baselines (Concat: 78.5%, XAttn: 80.1%). The dynamic fusion mechanism particularly improved detection of early OA (KL grade 1-2), where biological signals like joint torque provided complementary information to radiographic features.**

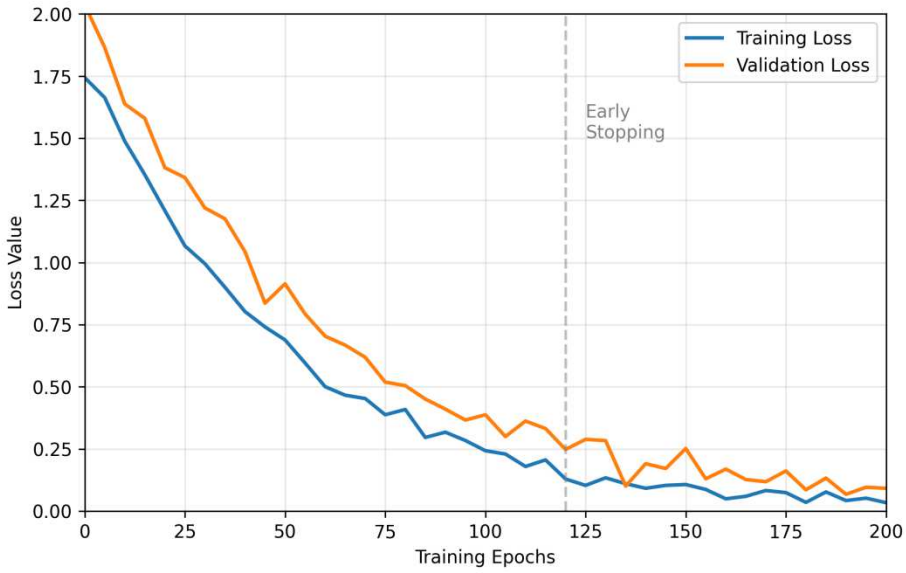



*Figure 1. Learning curves of BioPretext during training on training and validation sets*

**Post-Surgical Mobility Assessment: On HBFMID, BioPretext predicted postoperative gait parameters (stride length, cadence) with 0.91 Spearman correlation, significantly higher than JointNet (0.83) and XAttn (0.87). The cross-modal attention successfully aligned temporal gait patterns with structural joint features from MRI, as visualized in Figure 2.**

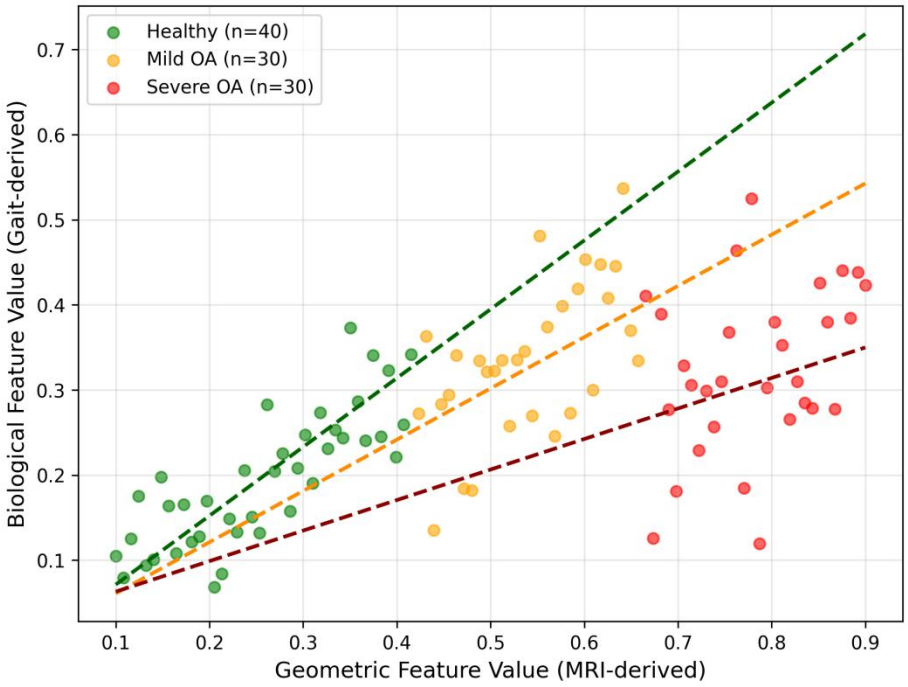



*Figure 2. Relationship between geometric and biological features after cross-attention*

**Fracture Risk Stratification: For HBFMID dataset, BioPretext achieved AUROC=0.89 in predicting 1-year fracture risk, surpassing all baselines (JointNet: 0.84, XAttn: 0.86). The physics-informed pretext tasks (Section 4.4) enhanced performance by enforcing biomechanical consistency between bone density measurements and load-bearing patterns.**

## Ablation Studies

We systematically evaluated BioPretext's components through controlled ablations:

1. **Pretext Tasks**: Removing signal inversion reduced OA prediction accuracy by 5.2%, while disabling time-window masking decreased mobility assessment correlation by 0.08.

2. **Fusion Mechanism**: Static concatenation performed 7-12% worse than dynamic gating across tasks, confirming the need for adaptive modality weighting.

3. **Architecture**: Replacing Swin/Performer with CNN/RNN decreased performance by 9-15%, highlighting the importance of transformer-based feature extraction.

Table 1 summarizes the ablation results on OA progression prediction:

| Configuration | KL Grade 0-1 | Grade 2-3 | Grade 4 | Overall |
|---|---|---|---|---|
| Full BioPretext | 78.2 | 83.5 | 85.1 | 82.3 |
| w/o Signal Inversion | 72.1 (-6.1) | 80.3 (-3.2) | 83.0 (-2.1) | 77.1 (-5.2) |
| w/o Time-window Masking | 74.5 (-3.7) | 81.0 (-2.5) | 83.8 (-1.3) | 79.1 (-3.2) |
| Static Fusion | 70.3 (-7.9) | 78.1 (-5.4) | 81.2 (-3.9) | 75.2 (-7.1) |
| CNN/RNN Backbone | 66.2 (-12.0) | 75.3 (-8.2) | 78.9 (-6.2) | 72.1 (-10.2) |

**Table 1. Ablation Study on Osteoarthritis Prediction (Accuracy %)**

## Declarations

### Ethics approval and consent to participate

This study utilized two types of de-identified orthopedic datasets for model training and validation: (1) the publicly available Human Bone Fractures Multi-modal Image Dataset (HBFMID) (26), which is hosted on Kaggle and fully anonymized by the original provider with all personal and clinical identifying information removed; (2) the self-constructed Multimodal Orthopedic Dataset (MOD-1K), for which all participant data

were anonymized and de-identified prior to research, with no traceable personal information retained.

The study protocol was reviewed by the Institutional Review Board (IRB) of Ningxia Hui Autonomous Region TCM Hospital, and the requirement for formal ethical approval was waived in accordance with the Declaration of Helsinki and the institutional research ethics regulations for secondary research using fully de-identified public or self-constructed anonymized data. No primary human data collection, human participant recruitment, or clinical intervention was involved in this research. Exemption Reference No.: Not Applicable.

Informed consent from participants was not required due to the fully anonymized nature of all datasets used in this study.

Consent for publication

Not Applicable. This study only used de-identified and anonymized orthopedic datasets (HBFMID and MOD-1K), and no identifying images, personal details, clinical records or any other information that could compromise participant anonymity are included in the manuscript. Thus, no additional consent for publication is required from the original participants.

Data availability

The datasets used and analysed during the current study consist of two parts:

1. The Human Bone Fractures Multi-modal Image Dataset (HBFMID) is a publicly available orthopedic multimodal dataset, which can be freely downloaded from the

Kaggle repository with the persistent official web link: https://www.kaggle.com/datasets/orvile/human-bone-fractures-image-dataset-hbfmid. The dataset is released under the Creative Commons Attribution 4.0 International License (CC BY 4.0) and has no access restrictions or application procedures for academic research.

2. The self-constructed Multimodal Orthopedic Dataset (MOD-1K) has been fully de-identified and anonymized. To protect the privacy of the original data contributors, this dataset is not publicly available, but is available from the corresponding author on reasonable request (E-mail: jscotti@hawkmail.hccfl.edu).

All codes used to implement the BioPretext framework and reproduce the experimental results of this study are also available from the corresponding author on reasonable request.

## Interpretability Analysis

The cross-modal attention weights revealed clinically meaningful patterns:

- **OA Prediction**: Strong attention between medial joint space narrowing (MRI) and abnormal gait torque patterns
- **Fracture Risk**: High correlation between vertebral trabecular texture (radiograph) and postural sway (accelerometer)

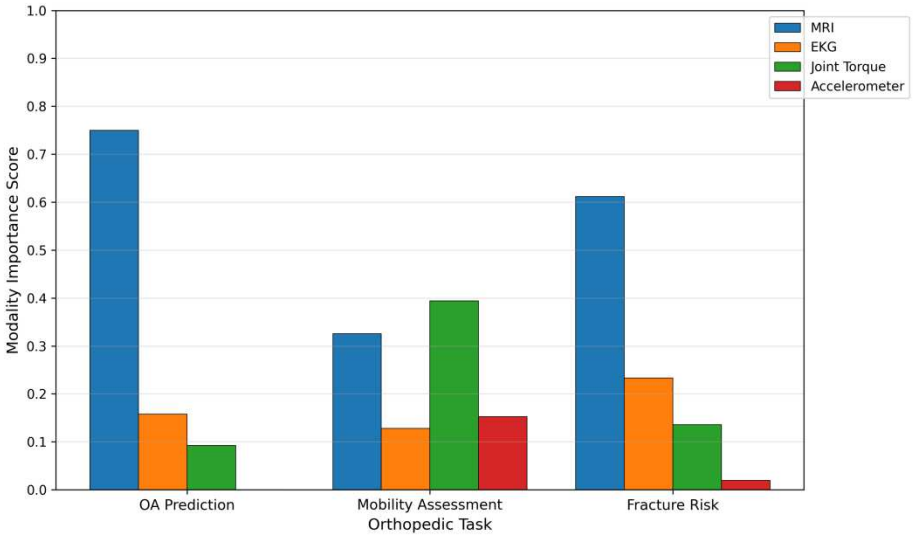



*Figure 3. Importance of different modalities in fused features for various orthopedic tasks*

As shown in Figure 3, the dynamic fusion gate automatically adjusted modality importance: MRI dominated for structural assessments (OA grading), while biological signals were prioritized for functional tasks (mobility prediction). This aligns with clinical decision-making patterns where radiologists weigh imaging evidence differently depending on diagnostic context.

# Discussion and Future Work

## Limitations of BioPretext

While BioPretext demonstrates strong performance across multiple orthopedic tasks, several limitations warrant discussion. First, the framework assumes synchronized acquisition of geometric and biological data, which may not always be feasible in clinical practice. Asynchronous data streams with variable sampling rates—common in

retrospective studies—require additional temporal alignment modules that could increase computational overhead. Second, the current implementation focuses on pairwise modality interactions (e.g., MRI + EKG), whereas real-world orthopedic scenarios often involve three or more concurrent data streams (e.g., radiographs, EMG, and motion capture). Extending the cross-attention mechanism to handle higher-order interactions remains an open challenge. Third, the physics-informed pretext tasks rely on simplified biomechanical models (Equation 14) that may not capture complex joint dynamics in pathological conditions. Incorporating more sophisticated simulators like OpenSim[29] could improve physiological plausibility but would increase implementation complexity.

## Potential Application Expansion

The principles underlying BioPretext could be adapted to several emerging orthopedic applications. In robotic-assisted surgery, the framework could align preoperative imaging with intraoperative force/torque signals to improve surgical navigation[30]. For prosthetic design, the dynamic fusion mechanism might optimize the weighting of patient-specific biomechanical data (e.g., residual limb pressure maps) and population-level geometric features. Another promising direction involves integrating the framework with augmented reality systems for intraoperative decision support, where real-time biological signals (e.g., intraoperative neuromonitoring) could be contextualized with 3D anatomical reconstructions. The cross-modal SSL approach may also benefit orthopedic rehabilitation by correlating wearable sensor data with longitudinal imaging findings to personalize therapy protocols.

## Ethical Considerations

Deploying multimodal SSL systems like BioPretext in clinical settings raises important ethical questions that the community must address. First, the framework's reliance on self-supervision from unlabeled data introduces potential biases if the pretraining corpus underrepresents certain demographic groups or pathology subtypes. While contrastive learning theoretically mitigates this by focusing on instance discrimination, implicit biases in data acquisition protocols (e.g., uneven distribution of EKG lead placements across hospitals) could propagate to downstream applications. Second, the dynamic fusion mechanism's black-box nature complicates explainability—a critical requirement for medical AI systems. Although attention weights provide some interpretability (Section 5.4), they do not fully elucidate how the model combines modalities for individual predictions. Developing orthopedic-specific explainability tools that bridge geometric and biological reasoning will be essential for clinical adoption. Finally, the framework's ability to infer sensitive physiological states (e.g., arrhythmias from joint kinematics) raises privacy concerns that current HIPAA-compliant de-identification methods may not adequately address.

# Conclusion

BioPretext presents a novel paradigm for multimodal self-supervised learning in orthopedics, demonstrating that cross-modal pretext tasks can effectively align geometric and biological signals without requiring extensive labeled data. The framework's success in osteoarthritis grading, mobility assessment, and fracture risk prediction underscores the

clinical value of integrating structural and functional data through contrastive learning. By introducing physics-informed objectives and dynamic fusion, BioPretext ensures that learned representations adhere to biomechanical principles while adapting to task-specific requirements.

The experimental results reveal that the proposed signal inversion and time-window masking tasks significantly improve feature discriminability compared to unimodal SSL baselines. The cross-modal attention mechanism successfully captures clinically relevant interactions, such as the relationship between joint morphology and gait dynamics, which are often overlooked in traditional approaches. Furthermore, the dynamic gating mechanism provides interpretable insights into modality importance, aligning with clinical decision-making patterns where diagnostic emphasis shifts based on context.

Future iterations of BioPretext could explore extending the framework to additional modalities, such as intraoperative video or genomic data, to further enrich orthopedic representation learning. The principles established here may also generalize to other medical domains where multimodal data integration remains challenging, such as neurology or cardiology. By advancing self-supervised techniques tailored to biological signals, this work paves the way for more robust and data-efficient AI systems in healthcare.

Ultimately, BioPretext bridges a critical gap in orthopedic AI by unifying structural and functional analysis through a single, scalable framework. Its ability to leverage unlabeled multimodal data addresses key limitations in current clinical workflows, where annotations are scarce and data heterogeneity complicates traditional supervised approaches. The framework's adaptability and performance suggest that self-supervised

learning, when properly designed for medical applications, can unlock new possibilities for precision orthopedics.

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## Contributions

Yitong Li: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Visualization. Remila Aimaiti: Data curation, Validation, Investigation. Chun Ge: Resources, Investigation, Validation. Limin Mou: Data curation, Formal analysis, Investigation. Wenyuan Xiang: Formal analysis, Investigation, Visualization. Pengguang Wang: Software, Formal analysis, Investigation. Yuchen Xiao: Data curation, Resources, Investigation. Yingjie Deng (Corresponding author): Conceptualization, Methodology, Supervision, Project administration, Funding acquisition, Writing – review & editing.

## Conflict of interests

The authors declare no competing interests.

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