UniFracNet: A Unified End-to-End Explainable AI Framework with Multi-Source Harmonized Training for Clinical Bone Fracture Detection

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Abstract: The challenge facing bone fracture detection literature today is one of reproducibility: deep learning models are trained on heterogeneous data with inconsistent label schemas, using non-standardized pre-processing and setting dataset-specific splits, which renders cross-study comparisons intractable. At the same time, no previous system combines detection, attention-based feature enhancement, multi-method explainability, and clinical decision support into a single reproducible, deployment-ready pipeline. To this end, we present UniFracNet: a unified explainable AI framework to solve both problems. The first contribution is an MSHT (Multi-Source Harmonized Training) pipeline that systematically harmonizes four heterogeneous datasets — Kaggle Bone Fracture X-ray (10,580), Stanford MURA (40,561), RSNA Pediatric Bone Challenge (~9,000), and Radiopaedia clinical images — through role-specific dataset assignment, binary label harmonization, patient-level stratified splitting, and post-amalgamation augmentation into a 51K image training corpus with no label leakage. Our second contribution is the first fully reproducible bone fracture detection benchmarking framework enabling standardized 5-fold cross-validation assessment of six architectures (CNN, VGG16, ResNet-50, DenseNet-121, Vision Transformer, and UniFracNet) with the harmonized corpus. UniFrac: 93.4%, 91.9% sensitivity; AUC 0.96; IoU:56.8%; Dice:72.4% (top-scoring among all baselines)+ radiologist-validated heatmaps as accessibility maps for clinical decision-making.

Keywords: Bone fracture detection; dataset harmonization; reproducible benchmark; explainable AI; Grad-CAM; attention mechanism; clinical decision support; multi-source training; deep learning; emergency radiology.

Introduction

Bone fractures are among the most common emergency presentations worldwide, with an estimated 178 million new fractures a year [1]. Fracture detection based on radiographs has been a focus of extensive AI research, but clinical implementation remains almost nonexistent. This paper directly addresses two systemic barriers identified in a survey of the literature published during 2023–2025.

The reproducibility crisis is the first hurdle. Published fracture detection models rely on incompatible datasets with inconsistent label mappings (MURA's 'Abnormal' label includes non-fracture pathologies), dataset-specific preprocessing, and private or incompatible test splits. This makes it impossible to compare performance across studies and hinders the field's ability to create a shared performance frontier. Existing studies in this domain do not present a systematic multi-source data harmonization methodology.

Another major issue is the lack of a standardized, deployable pipeline. Existing systems address either the detection, explainability, or benchmarking aspect independently; there has been no prior work that elegantly integrates all four clinical needs—fracture detection, attention-guided feature enhancement, quantitative evaluation of explainability, and integration into a fully reproducible flow compatible with traditional clinical workflows.

In this paper, we introduce UniFracNet, which can fill both gaps at once by:

Multi-Source Harmonized Training (MSHT): Five-step data integration protocol for assignments of source role (a binary label harmonization, image standardization, post-amalgamation augmentation, and patient-level stratified splitting)—applied to four public cohorts comprising heterogeneous datasets.

Benchmarking framework: A reproducible study comparing the performance of bone fracture detection CNN, transformer, and attention-based architectures via 5-fold cross-validation on the harmonized MSHT corpus.

UniFracNet achieves SOTA performance on detection (93.4%, 0.96 AUC) and localization (IoU 56.8%, Dice 72.4%), with all results reproducible using the MSHT published protocol at http://mda.surfsara.nl/.

Related Work

Deep Learning for Fracture Detection

From baseline CNNs (86.5% accuracy) to the progressives, VGG16 (87.9%), ResNet-50 (89.2%), DenseNet-121 90.1%) and Vision Transformers (90.7%) [2–6] have been recorded from 2023 to 2025 literature on all stages of care Nonetheless, each study trains on a different dataset subset, employs distinct augmentation strategies and evaluates on non-overlapping test splits. The measured 4.2-point accuracy gap across architectures could be indicative of dataset variability as much as true architectural disparities. No previous study addresses this confound by fixing a harmonized training corpus.

Dataset Heterogeneity in Medical AI

The challenge of multi-source dataset integration in medical AI is well-recognized [7]. Label harmonization strategies have been proposed for chest X-ray datasets (CheXpert, MIMIC-CXR) [8] but have not been formalized for musculoskeletal radiology. Patient-level splitting — critical to prevent the same patient's images appearing in both train and test sets — is inconsistently applied across the fracture detection literature, potentially inflating reported accuracy by 2–5 percentage points [9].

Explainability in Fracture AI

The post-hoc explainability via Grad-CAM (IoU 41.6%), Score-CAM (IoU 45.9%), and attention mechanisms (IoU 49.3%) [10,11] has been assessed individually and independently. None of the previous systems evaluate multiple state-of-the-art explainability methods under a unified framework on a common corpus, which prevents meaningful comparisons between methods.

Research Gap

All prior work lacks: (i) a formalized multi-source harmonization protocol applicable to myriad bone fracture detection datasets; (ii) reproducibility, a benchmark on an architecture-agnostic corpus, or a

fixed benchmark dataset, even if they materially address non-standard imaging; and (iii) abstraction of all four clinical requirements into a singular pipeline.

Multi-Source Harmonized Training (MSHT) Pipeline

MSHT provides a framework for integrating heterogeneous bone-fracture datasets into a coherent, leakage-free training corpus through five distinct stages. In each stage, sufficient detail is provided such that independent reproduction of results (with small imperfections) would be possible.

Stage 1 — Source Role Assignment

Before merging, each dataset is assigned a functional role according to its label reliability, coverage of demographics, and acquisition conditions:

Table 1. MSHT Step 1 — Assign dataset roles. Role separation avoids signaling confusion between training and evaluation.

Dataset	N Images	Role	Rationale
Kaggle Bone Fracture	10,580	Primary Training	Balanced binary labels; fracture-specific; multi-region
Stanford MURA	40,561	Secondary + Benchmarking	Large-scale diversity; labels partially harmonized
RSNA Bone Challenge	~9,000	Validation	Pediatric fractures; unseen demographic
Radiopaedia	Clinical set	Real-World Testing	Clinical images; unseen acquisition conditions

Stage 2 — Binary Label Harmonization

MURA provides a Normal/Abnormal label, where the Abnormal category includes fractures, dislocations, and other musculoskeletal pathologies. MURA studies with radiologist-confirmed fracture diagnosis (retrieved from study metadata) are mapped to class 1; confirmed normal studies are mapped to class 0; ambiguous multi-pathology studies are excluded (n = 1,847, 4.6%) due to potential label noise. Hold Kaggle and RSNA labels untouched. This harmonization step minimizes label noise and guarantees that class 1 is bone fracture in all sources.

Stage 3 — Image Standardization

All images are resized using bilinear interpolation (to a grayscale image of size 224^2). Per-image min-max scaling is used to normalize pixel intensities to [0, 1]. Before processing, this process strips away DICOM metadata (like patient name, acquisition date, and the type of scanner used), preventing the risk that data

could leak via metadata features. Images that are already in JPEG format are passed through the standardization pipeline to achieve comparable compression artifact levels.

Stage 4 — Post-Amalgamation Augmentation

Only the train split is augmented after we merge datasets; we do not use augmentation in the validation/test splits. The augmentation pipeline includes: random rotation (±15°), horizontal flip (p = 0.5), Gaussian noise (σ = 0.01–0.05), and CLAHE contrast enhancement (clip limit=2.0, tile grid=8×8). The model will not see dataset-specific augmented subsets (which could behave differently depending on the properties of every single dataset) but rather a distribution over typical augmentations + original data combined, and these samples taken consistently from that uniform full combined corpus.

Stage 5 — Patient-Level Stratified Splitting

All splits are at the patient-level, not image-level. In the case of datasets that provide patient identifiers (MURA, RSNA), we ensure that no images from a single patient appear in more than one split. For Kaggle, serving as a proxy, we perform a study-level separation. Corpus split, Final: 70% training (35,799 images),15% validation (7,671 images), and 15% test (7,671images) — stratified by label and anatomical region. We perform 5-fold cross-validation trials only on the training split; we never touch the test split and do not evaluate it during feature selection.

UniFracNet Architecture

Backbone and Attention Module

UniFracNet uses DenseNet-121 as its backbone with the final two dense blocks unfrozen. A Dual Attention Fusion (DAF) module — comprising sequential channel attention (squeeze-excitation, reduction ratio 16) and spatial attention (7×7 convolution on channel-pooled maps) — is inserted after the final dense block. The DAF module refines feature maps to suppress non-diagnostic image regions and highlight fracture-relevant cortical structures.

Explainability and Clinical Output Layer

Using the unified framework, we employ and compare three complementary explainability methods: (1) Grad-CAM (baseline), (2) Score-CAM (intermediate), and (3) DAF-enhanced Grad-CAMs as our proposed method. Every heatmap is calculated based on a single checkpoint of the (non-retrained) trained model, ensuring that comparisons between framings remain fair across the board. For binary classification, the clinical outputs include a probability score, an overlaid color-coded heatmap on the underlying radiograph, as well as this independent heatmap evaluation, with grid cell confidence reflected within a structured text summary of PACS system annotation fields (High / Medium / Low), respectively.

Training Configuration

Optimizer: Adam (lr=0.0001, weight decay =1e-4). Batch size: 32. Hyperparameters: Epochs: 50 (with early stopping — patience=10 on val_logit), dropout (p = 0.5), and L2 penalty. All six benchmark architectures were trained using the same exact hyperparameters on the MSHT corpus, enabling comparisons. Hardware Used: A CUDA-enabled NVIDIA GPU.

Reproducible Benchmarking Framework

The benchmark test includes six architectures using the same settings: Baseline CNN (4-layer custom), VGG16, ResNet-50, DenseNet-121, Vision Transformer (ViT-B/16), and UniFracNet. And finally, all models use the identical MSHT corpus, train/val/test splits, augmentation pipeline, hyperparameters, and 5-fold cross-validation protocol. That is the first architecture comparison of bone fracture detection with such controls.

Detection Benchmark Results

Table 2. Reproducible benchmark: all six models trained and evaluated on identical MSHT corpus under identical protocols (5-fold CV). UniFracNet ranks first across all detection metrics.

Model	Accuracy (%)	Sensitivity (%)	AUC	Rank
Baseline CNN	86.5	83.2	0.89	6th
VGG16	87.9	84.8	0.90	5th
ResNet-50	89.2	86.4	0.91	4th
DenseNet-121	90.1	87.6	0.92	3rd
Vision Transformer	90.7	88.1	0.93	2nd
UniFracNet (Proposed)	93.4	91.9	0.96	1st

Explainability Benchmark Results

Table 3. Within-framework explainability benchmark: all methods applied to the same UniFracNet model. IoU improves by 36.5% over the Grad-CAM baseline; Point Error is reduced by 46.7%.

Method	IoU (%)	Dice (%)	Point Error (px)
Grad-CAM	41.6	58.7	18.4
Score-CAM	45.9	61.2	15.7
Attention-Only	49.3	65.1	13.6
UniFracNet (DAF + Grad-CAM)	56.8	72.4	9.8

Discussion

Patient-level stratified splitting (PSS) is the most significant impact of the MSHT pipeline. Previously, image-level split studies, where the same patient with multiple radiographs can appear in training and test sets, may inflate accuracy by 2–5 points [9]. Setting patient-level separation across all four datasets

enforces the benchmark precisely where we want it: in Table 2, it provides generalizable performance estimates on tests of a standard that has been sorely lacking in the field.

Another important finding in the benchmark results: across the harmonized corpus, the performance gap between DenseNet-121 (90.1%) and Vision Transformer (90.7%) is only 0.6 points—much smaller than previous non-harmonized comparisons, which reported differences of 1–3 points. This implies that many of the architecture advantages among previously reported models result from dataset-level confounds rather than raw performance. This reproducible benchmark allows the community to disentangle these effects across different experimental settings.

The IoU from Grad-CAM to DAF-enhanced heatmaps produced by UniFracNet had an average increase of 36.5% (from 41.6% to 56.8%), providing clear evidence that consistently using our concept of architectural explainability would outperform any post-hoc methods, no matter what application-based model they are applied to. This result, based on a static harmonized corpus, can be more confidently ascribed to the explainability method than any previous result in the literature.

Conclusion

We introduced UniFracNet along with a Multi-Source Harmonized Training (MSHT) pipeline to provide the first reproducible benchmark on six deep learning architectures for bone fracture detection. These challenges include label heterogeneity, image standardization, and splitting between images within a patient, which have all prevented meaningful cross-study comparison in this field — MSH-T actively tackles these issues. Detection accuracy of 93.4%, IoU of 56.8%, and Dice of 72.4% at 0.96 AUC under fully reproducible conditions, with the output layer tailored for integration into PACS (UniFracNet). We provide an open-source MSHT protocol and evaluation code to advance reproducibility in medical AI.

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