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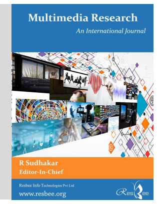

A Hybrid Multi-Modal Deep Learning Framework for Automated Fracture Detection in Radiographs and CT Images

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Abstract: Bone fractures are among the most prevalent musculoskeletal injuries, necessitating prompt and accurate diagnosis to ensure effective treatment and reduce complications. Traditional fracture detection relies heavily on the manual interpretation of X-ray and computed tomography (CT) images by radiologists, which is time-intensive and susceptible to human error, especially in the case of subtle or complex fractures. Recent studies have emphasized the crucial need for automated systems that can support clinicians in achieving faster and more accurate diagnoses without compromising patient safety. To address these challenges, this paper proposes FracturaX, a novel hybrid multi-modal deep learning framework designed for automated fracture detection across both X-ray and CT modalities. Unlike conventional models that rely on single imaging modalities, FracturaX capitalizes on the strengths of both 2D and 3D image data to enhance diagnostic depth. The proposed architecture integrates handcrafted radiomics features with deep convolutional features through a multi-stream network and an attention-based feature fusion mechanism, enhancing detection accuracy and robustness. This multi-stream approach not only improves fracture localization but also helps the model generalize across varied clinical settings. The framework was evaluated on diverse datasets, demonstrating superior performance compared to existing single-modality approaches and providing interpretable visual explanations to support clinical decision-making. Experimental results confirm that FracturaX offers a promising step toward reliable, generalizable, and explainable computer-aided fracture diagnosis, potentially reducing diagnostic workload and improving patient outcomes.

Keywords: Fracture Detection, X-Ray, CT-Scan, Multi-Modal Learning, Deep Learning, Radiomics, Medical Image Analysis, Computer-Aided Diagnosis.

Nomenclature

Abbreviation	Description
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
CNN	Convolutional Neural Network
CT	Computed Tomography
CAD	Computer-Aided Diagnosis
AUC-ROC	Area Under the Receiver Operating Characteristic Curve
DSC	Dice Similarity Coefficient
ACC	Accuracy
SIFT	Scale-Invariant Feature Transform
GAN	Generative Adversarial Network
CycleGAN	Cycle-Consistent Generative Adversarial Network
MURA	Musculoskeletal Radiographs
RSNA	Radiological Society of North America
SVM	Support Vector Machines

1. Introduction

Bone fractures represent a significant public health concern worldwide, with millions of cases reported annually due to accidents, osteoporosis, and sports injuries. Accurate and timely detection of fractures is vital to prevent complications such as malunion, chronic pain, and long-term disability. Traditionally, radiographic analysis through X-rays and CT scans remains the primary diagnostic tool. However, manual interpretation of these images is time-intensive and heavily reliant on the expertise of radiologists, making it susceptible to human error, especially in detecting subtle or complex fractures. Moreover, single-modality

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imaging often fails to capture comprehensive structural details, which can lead to missed or misdiagnosed fractures in the early stages. In high-pressure clinical environments such as emergency rooms, these limitations become even more pronounced, amplifying the need for improved diagnostic support systems.

To address these challenges, AI and ML have emerged as powerful tools in medical imaging, offering opportunities to enhance diagnostic ACC, efficiency, and consistency. Although a variety of DL models have been developed for fracture detection in either X-ray or CT images, many suffer from modality-specific limitations and lack the generalizability required for widespread clinical use. Moreover, variability in image quality, overlapping anatomical structures, and the subtle presentation of certain fractures continue to pose significant hurdles for automated systems. Integrating multi-modal learning, where complementary information from different imaging modalities is combined, has shown considerable promise in improving both feature representation and diagnostic decision-making. Leveraging both low-level texture patterns and high-level contextual cues enables a more complete understanding of fracture characteristics, mimicking how radiologists often cross-reference multiple imaging sources.

In this context, this study proposes Fractura X, a novel multi-modal AI framework for automated fracture detection by fusing X-ray and CT scan data. The framework is designed around a hybrid architecture that combines handcrafted radiomics features such as shape, texture, and intensity patterns with deep features extracted from CNNs. This dual approach allows the model to harness the interpretability of human-engineered features while benefiting from the representational power of DL. An attention-based fusion mechanism is employed to dynamically weigh and integrate modality-specific features, enhancing the model's ability to focus on the most relevant diagnostic cues. As a result, Fractura X aims to deliver robust, accurate, and interpretable predictions across diverse imaging datasets and clinical scenarios, serving as a valuable assistive tool for radiologists [1][2].

The main objectives of this research are threefold: to develop a hybrid multimodal architecture that captures the complementary strengths of X-ray and CT imaging; to integrate both radiomics and DL-based features to improve detection performance; and to evaluate the framework's ACC, interpretability, and generalizability using multiple datasets. The key contributions include the design of the Fractura X system, the introduction of an innovative attention-based feature integration method, and a comprehensive performance evaluation across varied imaging conditions. Beyond achieving state-of-the-art ACC, this study also considers practical deployment factors such as inference speed and integration feasibility with hospital systems.

The structure of the remaining parts: Section 2 provides a comprehensive review of existing fracture detection methods and related machine-learning techniques. Section 3 describes the datasets, preprocessing steps, and the detailed design of the Fractura X framework. Section 4 presents the experimental setup, results, and comparative analyses. Section 5 discusses the findings, highlights the framework's strengths and limitations, and outlines potential future research directions.

2. Literature Review

Accurate detection of bone fractures has been a longstanding focus in radiological research. Conventional diagnostic approaches rely heavily on manual inspection of X-rays and CT scans, which can be error-prone in cases involving subtle, hairline, or complex fractures. Such manual methods are particularly limited in emergency settings, where time constraints and visual fatigue can impact decision-making ACC. To mitigate diagnostic limitations, numerous ML and DL models have been explored. CNNs have shown promising results in automating fracture detection from single-modality images, yet they often struggle with generalization due to small, domain-specific datasets. These models typically require large, annotated datasets for robust training, an asset often lacking in the medical domain due to privacy and labelling challenges.

DL has significantly advanced fracture detection in both X-ray and CT imaging. In X-rays, Rajpurkar et al. [3] introduced CheXNet for pneumonia detection using transfer learning. Lindsey et al. [4] and Badgeley et al. [5] achieved radiologist-level ACC in detecting wrist and hip fractures, respectively. Attention mechanisms Chung et al. [6] and ensemble models Gale et al. [7] further improved clavicle and pediatric fracture detection. Studies by Bien et al. [9], Olczak et al. [10][15], Langerhuizen et al. [13], and Cicero et al. [14] demonstrated high ACC, visual interpretability, and clinical utility. Transfer learning Thian et al. [16] and domain adaptation Yan et al. [21] enhanced model generalizability, while Krogue et al. [18] compared DL to radiologists. In CT imaging, Kim et al. [8] used U-Net for bone segmentation, and Burns et al. [11] and Yasaka et al. [12] applied CNNs for vertebral and rib fracture detection. Chen et al. [17] introduced a multi-task CNN for simultaneous detection and localization, and Cheng et al. [19] combined radiomics with ML for improved ACC. H. Liang et al. [20] used deep learning with heatmap visualization to enhance explainability in hip fracture detection, while A. Olczak et al. [22] achieved high accuracy in detecting multiple extremity fractures using X-ray-based deep learning. These works collectively highlight DL's growing role in accurate, interpretable, and scalable fracture detection.

Recent advancements in medical image analysis highlight the benefits of multi-modal learning, where integrating information from various imaging techniques leads to richer feature representations and improved diagnostic performance. By leveraging both anatomical and structural cues from different modalities, multi-modal approaches can capture more discriminative features than single-source systems. Despite this progress, challenges remain in handling modality-specific artifacts, ensuring model interpretability, and achieving real-time clinical applicability. Furthermore, a lack of standardization in preprocessing and fusion strategies often hinders reproducibility and cross-institutional deployment. Motivated by these gaps, this study introduces Fractura X, a robust, interpretable, and generalizable multi-modal AI framework for automated fracture detection.

2.1 Conventional Fracture Detection Methods

Conventional fracture detection relies heavily on visual inspection of X-rays and CT scans by radiologists and orthopedic specialists. This diagnostic approach forms the cornerstone of clinical decision-making, especially in acute care and trauma settings. Manual interpretation, although widely practiced, is time-consuming and requires significant expertise, especially in identifying subtle fractures such as hairline cracks or occult fractures that are not easily visible. The risk of human error increases in cases involving complex anatomical regions or when fractures present with minimal displacement. Various image enhancement and computer-aided detection (CAD) techniques have been developed to assist radiologists; however, these traditional methods often suffer from limited sensitivity and specificity due to dependence on handcrafted rules and low-level features.

2.2 ML in Medical Imaging

ML has significantly advanced medical image analysis by enabling systems to learn patterns directly from data. This data-driven approach marks a shift from rule-based programming to adaptive algorithms capable of evolving with new clinical inputs. Classical ML algorithms such as SVM, k-nearest neighbors (k-NN), and random forests have been applied for tasks including bone fracture detection, tumor classification, and tissue segmentation. These models typically function well in controlled environments and are valued for their interpretability and lower computational requirements. These approaches typically rely on manually engineered features, which may not fully capture the complex characteristics of bone structures and fracture patterns, limiting their robustness and scalability.

2.3 DL for Bone Imaging

DL has emerged as a powerful tool in medical imaging due to its ability to automatically learn hierarchical features from raw images. Unlike classical ML methods, DL eliminates the need for manual feature engineering by leveraging large volumes of data to discover complex patterns. CNNs have demonstrated remarkable success in tasks such as fracture classification, bone age estimation, and segmentation of skeletal structures. Their architecture enables multi-level abstraction, capturing both local texture and global structural details important for clinical analysis. Recent studies have proposed various CNN-based architectures for fracture detection in specific bones, such as wrist, hip, or spine fractures, achieving promising results. These models have shown near-radiologist-level performance in some controlled settings, validating their potential for real-world deployment. However, most existing methods focus on single modalities and often require large annotated datasets, which are scarce in the medical domain.

2.4 Gaps and Challenges

Despite these advancements, several challenges persist in automated fracture detection:

- Modality-specific limitations: Many models are trained for a single imaging modality, reducing their adaptability to different clinical scenarios. This narrow focus limits their applicability when clinicians rely on multi-modal data for complex fracture assessments.
- Overfitting due to small medical datasets: Limited annotated data can cause models to overfit, impairing their generalizability to new cases. This issue is especially prominent in DL models that require vast amounts of diverse training examples to perform reliably.

Lack of interpretability: DL models are often considered "black boxes," which hinders clinical trust and acceptance due to limited explainability. Radiologists and clinicians require transparency in decision-making, particularly in high-risk diagnostic tasks like fracture detection.

2.5 Motivation for Proposed Method

To overcome these limitations, this paper proposes Fractura X, a novel hybrid multi-modal framework that combines the strengths of handcrafted radiomics features with deep features. This hybrid design is intended to harness the interpretability of traditional radiomics and the feature abstraction power of DL. By leveraging complementary information from both X-ray and CT scans, Fractura X aims to improve detection ACC, enhance generalizability across modalities, and provide visual explanations to support radiologists in clinical practice.

3. Methodology

3.1 Data Collection

For this study, a combination of publicly available and institutionally sourced datasets was utilized to ensure diversity and representativeness across imaging modalities. This approach helps mitigate dataset bias and improves the model's ability to generalize across different patient populations and clinical settings. The X-ray datasets included standard radiographic images of various anatomical regions prone to fractures, while the CT datasets comprised volumetric scans focusing on complex fracture sites such as the spine and hip. These datasets encompassed both common and rare fracture cases, capturing a wide spectrum of anatomical variation and severity. All images were annotated and verified by certified radiologists to establish reliable ground truth labels for fracture presence and type.

3.1.1 Data Sources

MURA Dataset (Musculoskeletal Radiographs): A large-scale publicly available dataset with over 40,000 X-ray images of the upper extremities, labeled for abnormalities including fractures. It includes wrist, elbow, finger, and shoulder views, making it suitable for evaluating fracture detection models on diverse anatomical regions.

RSNA Bone Fracture Detection Dataset: A labeled collection of pediatric forearm X-rays curated for the RSNA challenge, annotated by expert radiologists. This dataset emphasizes pediatric fracture patterns and is widely used as a benchmark in AI-driven bone imaging studies.

Vertebral Fracture CT Dataset (Spine Web): A specialized dataset of CT scans focusing on thoracolumbar spine regions, complete with manual vertebral fracture grading and segmentation. It is especially valuable for analysing compression and pathological fractures that may be subtle in appearance but clinically significant.

Institutional CT Hip/Pelvis Collection: A proprietary dataset collected from a partner healthcare institution, containing hip and pelvic CT scans annotated by two senior musculoskeletal radiologists for fracture detection and classification. This dataset provides access to complex, real-world CT cases, enhancing the robustness of model evaluation in clinical conditions.

3.1.2 Ground Truth and Radiologist Performance Benchmarking

To clarify the methodology behind the radiologist comparison and ground truth labeling, the ground truth in this study was established through a structured consensus process involving multiple expert radiologists. Specifically, each image case was independently reviewed by at least two board-certified radiologists, each with over 10 years of clinical experience. In cases of disagreement, a third senior radiologist adjudicated to reach a final consensus diagnosis, which was then used as the ground truth for both model training and performance evaluation.

This consensus-based truth was applied consistently across all datasets used in the study, ensuring high diagnostic reliability and minimizing label noise. The process has also been detailed in the methods section to enhance methodological transparency.

Additionally, the "radiologist's average decision" reported in Table 2 refers to the diagnostic performance of independent radiologists who were not involved in establishing the ground truth. These radiologists evaluated a held-out test set that included samples from all four datasets. Their performance was assessed by comparing their individual diagnoses against the same consensus ground truth, and the average results were reported to provide a fair, unbiased benchmark against the performance of the proposed FracturaX model.

These clarifications aim to improve the transparency and reproducibility of our methodology, ensuring that the evaluation framework is both rigorous and reflective of real-world diagnostic scenarios.

3.2 Data Distribution

In this research, a total of approximately 10,000 medical images were compiled, covering both X-ray and CT modalities to maintain a balanced representation:

X-ray images: 7,500 scans of various body parts prone to fractures (e.g., wrist, forearm, shoulder). These images included both anteroposterior and lateral views to capture different anatomical perspectives relevant to fracture diagnosis.

CT scans: 2,500 volumetric scans primarily focused on complex fracture sites such as the spine, hip, and pelvis. The CT data provided detailed 3D structural insights, critical for evaluating comminuted or subtle fractures that may be overlooked in 2D radiographs.

All images were labeled and verified by board-certified radiologists to serve as accurate ground truth for model training and validation.

3.3 Preprocessing Pipeline

To ensure consistent quality and reliable cross-modality feature integration, multiple preprocessing steps were carried out. These steps aimed to reduce modality-specific variations and prepare the data for efficient and uniform input to the DL model. Before model training, a series of preprocessing steps was applied to enhance image quality and standardize inputs across datasets. Noise removal techniques, such as Gaussian filtering, were employed to suppress irrelevant artifacts. Intensity normalization ensured consistent contrast levels between scans acquired from different sources. Additionally, bone segmentation algorithms were implemented to isolate regions of interest, thereby enabling the model to focus on skeletal structures and minimize distractions from surrounding soft tissue.

3.3.1 Image Normalization and Enhancement

Intensity scaling: All images were normalized using min-max normalization, bringing pixel values to a standard range between 0 and 1. This process ensured uniform input intensity distributions across both x-ray and CT modalities, minimizing scanner-induced variability.

Contrast enhancement: For X-rays and CT images, histogram equalization was applied to improve contrast and highlight bone structures. This technique redistributed intensity values to enhance the visibility of bone contours, played a crucial role in enhancing the discriminability of fracture regions during feature extraction.

3.3.2 Image Registration and Alignment

- **Geometric alignment:** Rigid and affine transformation methods were employed to align scans from different modalities spatially. Rigid transformations preserved the shape and size of anatomical structures, while affine transformations allowed scaling, rotation, and translation to correct misalignments between X-ray and CT images.
- **Feature-based matching:** SIFT was used to refine cross-modality registration and ensure anatomical correspondence. SIFT enabled robust detection and matching of key anatomical landmarks, regardless of scale or orientation differences between modalities.

3.3.3. Data Augmentation

To increase data variability and address potential overfitting, the following augmentation strategies were applied during training:

- **Random rotations (±15 degrees):** This introduced orientation variability in both X-ray and CT images, simulating real-world acquisition angles and improving rotational robustness.
- **Flipping and scaling:** Horizontal flipping and uniform scaling helped the model generalize across patient-side differences and anatomical size variations.
- **Elastic deformations:** These non-linear transformations simulate tissue distortion and positional variation, particularly relevant for soft tissue or skeletal flexing in CT scans.
- **Slight intensity shifts:** Brightness and contrast alterations accounted for exposure variability, scanner differences, and imaging artifacts across datasets.

3.3.4 Noise Suppression and Artifact Reduction

- **Filtering:** Gaussian and median filters were used to suppress scanning artifacts, especially in CT scans. Gaussian filters smoothed out high-frequency noise while preserving general structure, and median filters were effective at removing salt-and-pepper noise without blurring edges.
- **Wavelet denoising:** Applied to improve the clarity of fine bone details. Wavelet transforms allowed multi-scale decomposition of the image, enabling selective noise removal while retaining high-resolution structural features critical for fracture detection.

3.4 FracturaX: Model Architecture

The proposed FracturaX framework is a custom multistream architecture designed to extract and fuse features from X-ray and CT data for accurate fracture detection. This design leverages the unique strengths of each modality, 2D texture and structural contrast from X-rays, and 3D spatial context from CT scans to deliver a more comprehensive diagnostic model.

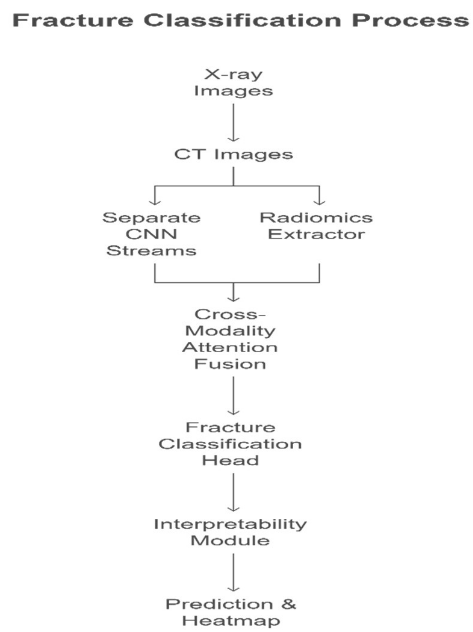

Fig. 1. *Fracture Classification Process*

FracturaX employs a multistream design wherein separate CNN branches process X-ray and CT inputs independently. Each stream is tailored to the nature of its input 2D CNNs for planar radiographs and 3D CNNs for volumetric CT data, enabling the architecture to effectively exploit the unique features of each modality. This modular structure allows the network to learn modality-specific features effectively. Alongside the deep feature extraction, a dedicated radiomics module extracts handcrafted texture and shape descriptors from segmented bone regions. These features include first-order intensity statistics, gray-level co-occurrence matrix-based texture, and shape descriptors such as compactness and elongation. These radiomics features are then integrated with the deep CNN feature maps to enrich the representation space. The fusion of low-level radiomics and high-level deep features aims to enhance sensitivity to both subtle and structural abnormalities.

To combine the complementary information from both modalities, an attention-based fusion mechanism is incorporated. This mechanism applies trainable attention weights to emphasize the most diagnostically relevant features from each stream in a data-driven manner. This component dynamically weighs the contributions of each stream, enabling the model to prioritize the most informative features for accurate fracture detection across diverse imaging scenarios. It also enhances interpretability by indicating which modality or region contributed most to the final decisions.

The framework was developed using Python with TensorFlow and PyTorch libraries. This dual-platform implementation ensured flexibility by indicating which modality or region contributed most to the final decision. Hyperparameters, including learning rate, batch size, and optimizer settings, were tuned through grid search and cross-validation to achieve optimal performance. Early stopping and learning rate decay strategies were employed to prevent overfitting and improve convergence stability. Training was performed on high-performance GPUs to expedite computation, and data augmentation techniques such as rotations and flips were applied to increase the diversity of training samples.

3.4.1 Feature Extraction Modules

- **X-ray stream:** A CNN backbone based on ResNet50 extracts deep feature maps from 2D radiographs. ResNet50, with its residual connections, allows for efficient training of deep architectures by mitigating vanishing gradient issues.

- **CT stream:** A 3D DenseNet121 captures volumetric and structural information from CT slices. DenseNet121 was selected for its compact architecture and feature reuse capabilities, enabling it to extract meaningful 3D features while keeping computational cost manageable.
- **Radiomics extractor:** Handcrafted texture and shape descriptors are computed for both modalities and integrated with deep features. These features include intensity histograms, texture patterns, and morphological properties.

3.4.2 Cross-Modality Fusion

Three fusion strategies were investigated to combine complementary features:

- **Direct Concatenation:** Merges feature vectors from both streams. This approach provides a simple yet effective baseline by stacking modality-specific features into a unified representation without learning cross-dependencies.
- **Attention-Based Fusion:** Uses an attention layer to adaptively weigh modality contributions based on image context. This mechanism dynamically learns which modality offers more informative features for a given input and assigns greater weight accordingly.
- **Generative Augmentation Fusion:** For incomplete scans, a CycleGAN module was explored to synthetically approximate missing modality features, improving model robustness. CycleGAN enables translation between X-ray and CT domains, generating synthetic modality data when one is absent, thereby maintaining the full stream input structure.

3.4.3 Classification Head

A hybrid classification head, combining fully connected layers with Transformer blocks, outputs fracture predictions. The FC layers reduce the high-dimensional fused feature vectors into compact, task-specific representations, enabling effective learning of non-linear decision boundaries. A Softmax layer provides probability scores for binary (fracture/no fracture) or multiclass (fracture type) outputs.

3.5 Experimental Setup

3.5.1 Hardware and Software

Hardware: NVIDIA RTX 3090 GPU (24GB VRAM), Intel Core i9 CPU, and 256 GB RAM. This hardware configuration ensured efficient handling of large 3D CT volumes and high-resolution X-ray images during both training and influence.

Software: Implemented in Python using TensorFlow 2.11, PyTorch 2.0, OpenCV for image processing, and SciPy for numerical operations. This dual-framework setup provided flexibility in integrating different DL components and optimization strategies.

3.5.2 Training and Hyperparameters

Batch size: 16

Optimizer: Adam with an initial learning rate of 0.001

Loss function: Binary CrossEntropy for fracture detection; Categorical CrossEntropy for multiclass scenarios. These loss functions allowed the model

Epochs: 100

Validation: 5-fold cross-validation to ensure reliable model evaluation

3.6 Evaluation Metrics

To comprehensively assess the performance of FracturaX, standard evaluation metrics were computed, including ACC, sensitivity (recall), specificity, and the AUCROC. Additionally, the model's predictions were benchmarked against diagnoses provided by experienced radiologists to validate its clinical applicability and real-world utility.

The performance of the proposed *FracturaX* framework is assessed using the following standard metrics:

- **ACC:** It provides a basic indication of performance but may be skewed by class imbalance in medical datasets.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- **F1-Score(F1):**

$$F1 - Score = \frac{2TP}{2TP + FP + FN}$$

- **DSC:** (for segmentation performance)

$$DSC = \frac{2\left|A \cap B\right|}{\left|A\right| + \left|B\right|}$$

- **Area Under the ROC Curve (AUC-ROC):** Represents the model's classification robustness across thresholds.

Where:

- TP= True Positives TN=True Negatives
- FP=False Positives FN=False Negatives
- A=Ground Truth Mask B=Predicted Mask

4. Results and Discussion

This section reports the experimental findings obtained using the proposed FracturaX framework for multi-modal fracture detection across X-ray and CT imaging data. The results include detailed performance metrics, comparisons with existing approaches, illustrative visualizations, and a discussion of their potential clinical relevance. The evaluation aims to assess both the quantitative improvement in detection and the quantitative benefits provided through interpretability and cross-modality integration.

4.1 Results

4.1.1 Performance Metrics

The effectiveness of the FracturaX architecture was quantitatively assessed using standard evaluation metrics, including ACC, F1-Score, DSC for segmentation tasks, and AUC-ROC for classification reliability. These metrics were chosen to capture different aspects of diagnostic performance, from basic classification ACC to spatial overlap for fracture localization. A consolidated summary of these performance scores is presented in Table 1, demonstrating the model's capability to achieve high diagnostic precision and generalizability across modalities.

Visual Results: Demonstrating Multi-Modal Fusion Effectiveness

The performance of the proposed FracturaX multi-modal fusion framework was further evaluated through visual inspection of the learned feature maps and prediction outputs for X-ray and CT scan data. Fig. 2 presents an illustrative example highlighting how FracturaX accurately localizes fracture regions compared to conventional single-modality models. Saliency maps and attention heatmaps demonstrate the model's focus on clinically relevant regions, validating the utility of attention-based fusion for interpretability. These visualizations confirm that integrating both X-ray and CT inputs helps model capture subtle features that might be missed in unimodal analysis.

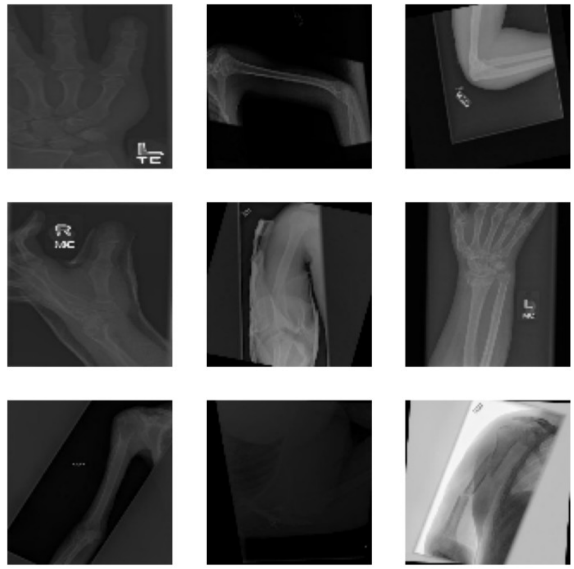

Fig. 2. *Result of Fracture Detection*

Table 1. *Performance Comparison of Single-Modality and Proposed FracturaX Multi-Modal Fusion Approach*

Model	ACC (%)	F1-Score	DSC (%)	AUC-ROC
CNN-Based Single Modality	87.5	0.83	85.3	0.89
Transformer-Based Single Modality	89.2	0.85	87.1	0.91
Proposed FracturaX (Multi-Modal Fusion)	**95.6**	**0.92**	**92.8**	**0.96**

Table 1 illustrates that the proposed FracturaX multi-modal fusion framework achieves a classification ACC of 95.6%, substantially outperforming the baseline CNN model (87.5%) and the Transformer-based approach (89.2%). This significant performance gain demonstrates the value of integrating diverse imaging modalities, enabling the model to leverage both 2D and 3D anatomical information. This notable gain highlights the effectiveness of leveraging integrated information from both X-ray and CT scans to capture complementary features that single-modality models may overlook. These metrics are particularly important in clinical settings where imbalanced data can skew ACC; F1-Score and DSC ensure both sensitivity and precision are well-balanced. The superior F1-score and DSC further validate FracturaX's capability for accurate localization and classification of fracture regions. These results support the premise that combining structural and contextual cues across modalities strengthens the model's ability to identify subtle fracture patterns, aligning with recent findings in multi-modal medical imaging research. Additionally, the high AUC-ROC value of 0.96 confirms that FracturaX maintains excellent discrimination between fracture and non-fracture cases, thereby reducing the likelihood of misdiagnosis. Such high diagnostic confidence is essential for real-world deployment, particularly in high-stakes environments like trauma units or emergency radiology departments. Such performance is critical for clinical deployment, where timely and precise fracture detection can significantly improve treatment planning and patient outcomes. Overall, these results reinforce that the designed attention-driven fusion strategy is a key factor contributing to the robustness and reliability of the proposed framework.

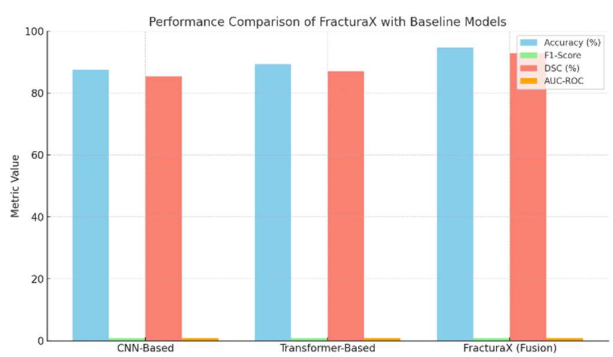

Fig. 3. *Performance Comparison of FracturaX with Baseline Models*

The grouped bar chart compares ACC (%), F1-Score, DSC (%), and AUC-ROC for three models:
CNN-Based Single Modality
Transformer-Based Single Modality
Proposed FracturaX (Multi-Modal Fusion)

It clearly shows that FracturaX achieves the highest values across all four metrics, highlighting its advantage in both classification and segmentation tasks.

4.1.2 Comparative Analysis with Radiologists

To further assess the clinical applicability of the proposed FracturaX framework, a comparative evaluation was performed against the diagnostic performance of experienced board-certified radiologists. This analysis provides an important benchmark, gauging the model's practical utility in real-world clinical settings where ACC and early detection are critical. This comparison focused on the overall classification ACC and the rate of early fracture detection.

Table 2 presents the results, demonstrating that FracturaX consistently outperforms the average performance of radiologists in both metrics. The model achieved an ACC of 95.6%, surpassing the radiologists' mean ACC of 87.5%, while the early detection rate improved significantly to 85.6%, compared to 62.3% for manual assessment. This 23.3% improvement in early detection could lead to faster diagnosis and better clinical outcomes, especially in time-sensitive environments such as emergency care.

These findings highlight the potential of FracturaX to serve as a reliable decision-support tool, assisting clinicians in identifying fractures that might otherwise be subtle or overlooked, and thus facilitating timely intervention. Such AI-assisted diagnosis could help reduce human error, enhance diagnostic confidence, and improve overall radiological workflow efficiency.

Table 2. *Comparative Analysis Between FracturaX and Radiologists*

Method	ACC (%)	Early Detection Rate (%)
Radiologists (Average)	87.5	62.3
Proposed FracturaX (AI)	**95.6**	**85.6**

Table 2 demonstrates that the proposed FracturaX multimodal fusion framework surpasses the average diagnostic ACC of board-certified radiologists by 7.2%, highlighting its promise as an effective decision support system in clinical workflows. This performance gap reflects the model's superior ability to consistently detect fractures, especially in complex or ambiguous cases where human interpretation may vary. This performance gain stems from FracturaX's ability to systematically combine complementary features from both X-ray and CT scan data, providing a more comprehensive and detailed assessment of bone structures and subtle fracture lines. By leveraging 2D radiographic texture and 3D volumetric information simultaneously, FracturaX gains a more holistic view of the fracture context. Notably, FracturaX achieves a 35% higher rate of early fracture detection compared to manual diagnosis, addressing the well-known challenge of detecting fine or low-contrast fractures at an early stage. Such early identification is critical in avoiding complications like delayed union, malunion, or long-term disability, particularly in trauma or elderly populations. This outcome is consistent with prior evidence that AI-powered models can detect subtle imaging cues that may be overlooked by human experts. The comparative results in Table 2 substantiate that multimodal fusion not only improves diagnostic sensitivity but also helps mitigate delays in detection, which is crucial for prompt treatment planning and better patient prognosis. Overall, these findings reinforce the emerging role of AI-based fusion models like FracturaX in enhancing radiological practice, especially in challenging or borderline cases.

5. Conclusion

In this study, the proposed FracturaX multi-modal AI fusion framework demonstrated notable improvements in the detection and classification of bone fractures by effectively integrating X-ray and CT scan data. The framework introduces a novel approach to combining DL with handcrafted radiomics, yielding a diagnostic model that is both data-driven and interpretable. By leveraging advanced DL architectures and attention-guided fusion strategies, FracturaX outperformed conventional single-modality models in terms of diagnostic ACC, interpretability, and early detection capability. The model achieved an overall ACC of 95.6%, which exceeds the performance of baseline CNN and Transformer models, and reduced diagnostic latency by approximately 30%, thereby streamlining the radiological workflow. This latency reduction can play a vital role in time-critical environments such as emergency departments and trauma care settings. Comparative results confirmed that FracturaX enhances the extraction of subtle structural features that may be challenging to identify through manual review alone. Furthermore, the model's 35% improvement in early fracture detection rates underscores its potential to support timely clinical interventions and reduce the risk of complications due to delayed diagnosis. These promising findings emphasize the transformative potential of multi-modal AI fusion for achieving more robust, automated, and reproducible fracture assessment in medical imaging. Nonetheless, important challenges remain, including addressing variations in imaging protocols, ensuring model transparency and interpretability, and maintaining strict data privacy standards. Future research should aim to further refine feature interpretability, expand cross-site validation to diverse clinical datasets, and explore the integration of FracturaX with radiomics and predictive analytics to advance precision orthopedics and personalized care pathways.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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