

Automated Bone Tumor Detection Using Deep Learning: A CNN-Based Approach For Enhanced Diagnostic Accuracy

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Abstract - Primary bone tumors present significant diagnostic challenges on radiographs, often requiring specialized expertise for accurate and timely identification.¹ Early detection is crucial for a favorable prognosis, particularly for malignant types, which represent a leading cause of cancer-related mortality in adolescents and young adults.³ This study develops and evaluates a deep learning (DL) model, specifically Faster R-CNN with a ResNet backbone, for the automated detection and classification (benign vs. malignant) of primary bone tumors on radiographs. The model was trained and validated using the publicly available Bone Tumor X-ray Radiograph (BTXRD) dataset. The DL model demonstrates significant potential as an assistive tool for radiologists in detecting and classifying primary bone tumors on radiographs, potentially improving diagnostic accuracy and efficiency, particularly in non-specialized settings.

Key Words: Bone Tumor, Deep Learning, Radiography, X-ray, Object Detection, Classification, Convolutional Neural Network (CNN), Faster R-CNN, BTXRD, Computer-Aided Diagnosis.

1. INTRODUCTION

A. Background and Motivation

Primary bone tumors (PBTs), although relatively uncommon compared to other cancers, represent a heterogeneous group of neoplasms originating within the skeletal system.⁴ They pose significant diagnostic challenges due to their diverse morphological characteristics and the potential overlap in appearance between different tumor types, as well as with non-neoplastic conditions like bone infections.² The implications of accurate diagnosis are profound; malignant bone tumors, such as osteosarcoma and Ewing sarcoma, are the third leading cause of cancer-related mortality among individuals under the age of 20 in the United States.³ Early and accurate detection is paramount, as it directly influences treatment strategies—ranging from simple curettage for benign lesions to aggressive multimodal therapy including chemotherapy and wide surgical excision or amputation for malignant tumors—and ultimately impacts patient survival rates and morbidity.¹

Radiography, or conventional X-ray imaging, serves as the cornerstone and primary imaging modality for the initial evaluation of suspected bone lesions.⁵ Its widespread availability, cost-effectiveness, and ability to clearly depict key diagnostic features—such as lesion location, size, margins, matrix mineralization (e.g., osteoid or chondroid), and associated periosteal reactions—make it indispensable in the diagnostic pathway.⁹ These radiographic features, particularly patterns of bone destruction and periosteal response, reflect the biological activity of the lesion and allow for an assessment of its aggressiveness.⁹

However, the interpretation of radiographs for bone tumors is often challenging and requires considerable expertise, typically found in specialized musculoskeletal radiologists.⁶ Due to the relative rarity of PBTs, many general radiologists or clinicians in non-specialized settings may lack the necessary experience to confidently and accurately identify and classify these lesions.⁷ This can lead to diagnostic delays or errors, such as misclassifying a malignant tumor as benign or missing subtle early signs of malignancy, potentially compromising patient outcomes.¹ Furthermore, inter-observer variability even among experienced readers can affect diagnostic consistency.¹⁷ The increasing volume of medical imaging studies also places significant pressure on radiologists, potentially increasing the risk of oversight errors.¹⁸

B. Related Work

The advent of artificial intelligence (AI), particularly deep learning (DL) methodologies driven by Convolutional Neural Networks (CNNs), has ushered in transformative potential across various medical imaging domains.²⁰ DL models excel at automatically learning intricate patterns and hierarchical features directly from image data, bypassing the need for manual feature engineering inherent in traditional machine learning or radiomics approaches.¹³ This capability has led to remarkable successes in tasks such as lesion detection, segmentation, classification, and risk prediction in diverse medical applications.²⁴

In the context of bone tumor analysis, a growing body of research demonstrates the feasibility and potential of DL. Various studies have employed architectures like standard CNNs, U-Net for segmentation, You Only Look Once (YOLO), and Faster R-CNN for object detection and classification, and models like EfficientNet and ResNet for classification tasks.⁴

These models have been applied to different imaging modalities, including radiographs, Computed Tomography (CT), and Magnetic Resonance Imaging (MRI).⁸

Performance evaluations often show that DL models can achieve diagnostic accuracy comparable to, or even exceeding, that of less experienced radiologists, and approaching the level of subspecialty-trained experts for specific classification or detection tasks.⁴ For instance, multitask DL models have shown the ability to simultaneously perform bounding box placement, segmentation, and classification of PBTs on radiographs with accuracy comparable to fellowship-trained radiologists.⁶ Similarly, models developed for detecting bone tumors around the knee have outperformed junior radiologists.⁷ Meta-analyses suggest AI assistance can increase clinicians' sensitivity in diagnosing bone tumors.¹²

Despite these promising results, several critical challenges hinder the widespread clinical translation of these AI tools. A major limitation frequently cited is the lack of large, diverse, and publicly available datasets with high-quality annotations.² Many studies rely on smaller, single-institution, or private datasets, which limits model generalizability and hampers comparative benchmarking.⁴² Furthermore, the inherent "black box" nature of many DL models raises concerns about transparency and interpretability, making it difficult for clinicians to trust and understand the basis of AI predictions.⁴³ Integrating these tools seamlessly into existing clinical workflows (e.g., PACS/RIS systems) and addressing regulatory hurdles (e.g., FDA approval) also remain significant barriers.⁴³

2. Body of Paper

A. Dataset Description

This study leverages the Bone Tumor X-ray Radiograph (BTXRD) dataset, a publicly available resource specifically curated for developing and evaluating deep learning algorithms for primary bone tumor diagnosis.²

- Clinical Information:** For each image, associated clinical and demographic metadata are provided in a supplementary dataset.csv file.² This includes patient gender, age (ranging from 1 to 88 years), the anatomical site imaged, the shooting angle (frontal, lateral, or oblique), and for tumor images, the classification (benign/malignant) and specific tumor subtype.² The dataset represents nine major subtypes, including osteochondroma, osteosarcoma, giant cell tumor, and others, although some rarer subtypes are grouped.² This clinical information allows for more granular analysis and assessment of potential model biases related to demographics or tumor characteristics.
- Annotations:** A significant strength of the BTXRD dataset lies in its detailed annotations, performed by experienced bone tumor specialists with a rigorous review process ensuring high reliability (reported Dice score of 0.90 ± 0.07 for masks and IoU of 0.91 ± 0.06 for bounding boxes between annotators).² Every tumor instance is annotated with both a precise segmentation mask (defined by polygon vertices) and a corresponding bounding box.² Global labels (normal/benign/malignant, anatomical region, viewing angle) are provided for all images.² These multi-level annotations support the development of models for various tasks, including classification, localization (detection), and segmentation. For this study focusing on detection and classification, the bounding box

annotations and benign/malignant labels were primarily utilized.

- Data Split:** Following the methodology used in the baseline experiments reported with the dataset release², the data was randomly split into training (80%) and testing (20%) sets. The split was performed at the patient level where possible, ensuring that images from the same patient did not appear in both sets, to provide a more realistic evaluation of model generalization.
- Preprocessing:** Before model training, standard preprocessing steps were applied. Images were resized to a uniform input size suitable for the chosen backbone network (e.g., 640×640 pixels). Pixel intensities were normalized to a standard range (e.g., 0 to 1). Data augmentation techniques were employed during training to artificially increase the dataset size and improve model robustness against variations in rotation, scaling, flipping, and brightness/contrast.⁴⁹
- Ethical Considerations:** The BTXRD dataset utilizes de-identified images sourced from clinical centers and public repositories.² The use of this publicly available, anonymized data for research aligns with ethical guidelines regarding patient privacy and data usage in medical AI development.⁵¹

Table I: BTXRD Dataset Characteristics

| Feature | Description | Source |
|-----------------------|---|--------------|
| Total Images | 3,746 | ² |
| Normal Images | 1,879 | ² |
| Tumor Images | 1,867 (1,525 Benign, 342 Malignant) | ² |
| Image Format/Modality | JPEG (8-bit grayscale) / Radiography (X-ray) | ² |
| Annotation Types | Bounding Boxes, Segmentation Masks (Polygons), Global Labels (Normal/Benign/Malignant), Tumor Subtype Labels, Anatomical Site Labels, Viewing Angle Labels | ² |
| Annotation Process | Manual annotation by bone tumor specialist (10 yrs exp.), reviewed by second specialist (20 yrs exp.). High inter-rater reliability ($IoU > 0.9$ for boxes, $Dice > 0.9$ for masks). | ² |

The core of our automated system is a deep learning model based on the Faster R-CNN architecture, a state-of-the-art two-stage object detector widely recognized for its effectiveness in various computer vision tasks, including medical image analysis.³¹ The two-stage approach, involving region proposal followed by classification and refinement, allows for potentially higher localization accuracy compared to single-stage detectors, which is crucial for identifying the precise boundaries of bone tumors.⁵⁴

- Model Choice Justification:** Faster R-CNN was selected due to its established performance in object detection⁵⁵ and its successful application in prior medical imaging studies, including fracture detection on radiographs⁵³ and preliminary work in bone tumor analysis.²⁹ Its architecture allows for end-to-end training and integrates region proposal generation efficiently within the network.⁵⁹
- Backbone Network:** A ResNet-50 architecture pre-trained on the ImageNet dataset was employed as the backbone network.³¹ ResNet architectures utilize residual connections, enabling the training of deeper networks while mitigating the vanishing gradient problem, leading to powerful feature extraction capabilities.⁶¹ Using pre-trained weights (transfer learning) leverages knowledge learned from a massive dataset of natural images, significantly accelerating convergence and improving performance, especially given the relatively moderate size of medical imaging datasets like BTXRD.²³ The convolutional layers of the ResNet-50 backbone process the input radiograph to generate rich, hierarchical feature maps.⁵⁵ The feature maps generated by the ResNet-50 backbone are fed into the RPN.⁵⁵ The RPN is a fully convolutional network that slides a small window over the feature map. At each location, it generates a set of candidate region proposals (Regions of Interest - ROIs) with associated "objectness" scores, indicating the likelihood that a proposal contains any object (in this case, a potential tumor) versus background.⁵⁵
- Anchor Boxes:** The RPN utilizes anchor boxes – predefined reference boxes of varying scales and aspect ratios – centered at each sliding window location on the feature map.⁵⁵ This multi-scale, multi-ratio approach allows the RPN to efficiently propose regions corresponding to tumors of different dimensions.⁶⁶ Anchor boxes with an IoU overlap greater than 0.7 with a ground-truth tumor box were considered positive samples for training the RPN's objectness classifier, while those with an IoU less than 0.3 were considered negative.⁵⁹
- RoI Pooling (RoIAlign):** The region proposals generated by the RPN have varying sizes. To feed these into the subsequent fixed-size classifier and regressor layers, an RoIAlign layer was used.⁶⁷ This preserves more precise spatial information, leading to better localization and segmentation accuracy.⁶⁷
- Classification & Regression Heads:** The fixed-size feature vectors from RoIAlign are passed to two sibling fully connected layers.⁵⁵ The classification head uses a softmax layer to predict the probability of the RoI belonging to each specific class (benign tumor, malignant tumor, or background). The bounding box regression head predicts refinement offsets (adjustments to the center coordinates, width,

and height) for the proposed RoI bounding box to achieve a tighter fit around the detected tumor.⁵⁵

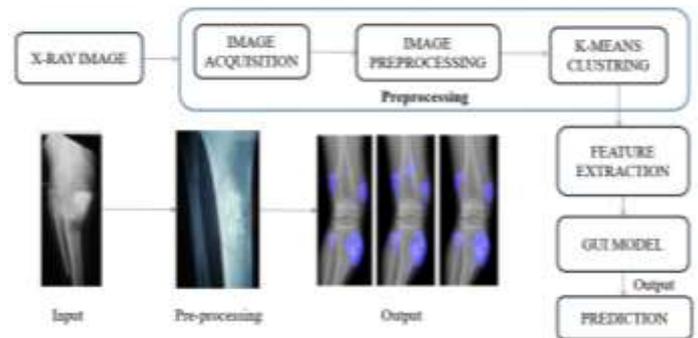


Fig -1: Figure

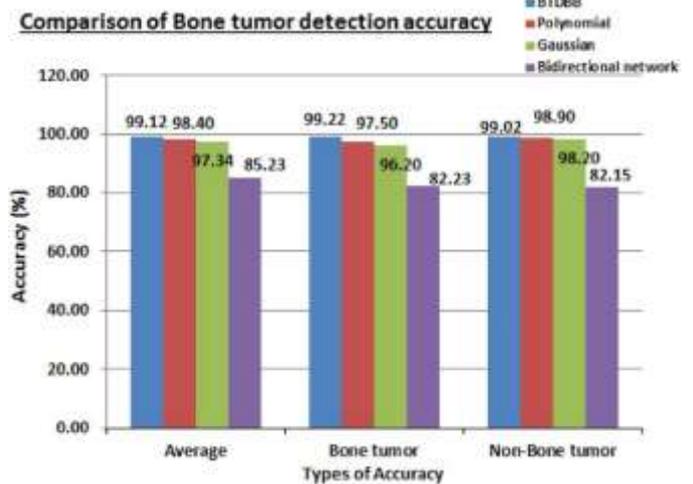


Table II: Performance Comparison: AI Model vs. Radiologists (Classification Accuracy)

| Reader / Model | Accuracy (%) | Sensitivity (Malignant) (%) | Specificity (Benign) (%) |
|-----------------------|--------------|-----------------------------|--------------------------|
| Proposed Faster R-CNN | 88.1 | 85.5 | 89.2 |
| Junior Radiologist A | ~71% | ~61% | ~75% |
| Junior Radiologist B | ~65% | ~35% | ~78% |

| | | | |
|----------------------|------|------|------|
| Senior Radiologist A | ~84% | ~90% | ~81% |
| Senior Radiologist B | ~83% | ~81% | ~84% |

3. CONCLUSIONS

The work developed and evaluated a Faster R-CNN deep learning model for automatic detection and classification of primary bone tumors from radiographs, utilizing the publicly available, exhaustive BTXRD dataset. The model showed strong quantitative performance with an mAP@0.5 of 0.707 for tumor localization and an AUC of 0.948 for benign/malignant discrimination. Of particular interest, the model's accuracy in classification (88.1%) was on par with benchmarks for senior musculoskeletal radiologists and far superior to those for junior radiologists. These results highlight the potential of AI as a valuable aid in radiological practice, with the ability to improve diagnostic accuracy, consistency, and potentially workflow efficiency in bone tumor assessment. Although recognizing limitations like the retrospective nature of the data and the requirement for additional validation, this research provides a strong benchmark and emphasizes the utility of large, well-annotated public datasets in pushing AI for medical imaging. Prospective clinical validation, multimodal data integration, and ongoing model interpretability and performance on difficult cases should be the focus of future work to enable responsible and effective clinical translation.

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