Deep Dive into Bone Tumor Segmentation and Classification: Methodological Review and Challenges with Deep Learning Approaches

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Abstract. This comprehensive review delves into the advancements made in utilizing Deep Learning (DL) procedures for bone tumor separation and classification. Bone tumors present a complex challenge in medical imaging due to their diverse morphological characteristics and potential for malignant behaviour. Traditional methods for tumor analysis often require extensive manual intervention and lack the efficiency needed for clinical applications. Deep learning approaches, with the accessibility of large-scale medical imaging datasets and sophisticated computer resources, have emerged as intriguing alternatives to solve these constraints. In this connection an attempt is made to review synthesizes recent developments in deep learning architectures, tailored specifically for bone tumor segmentation and classification tasks. Additionally, it examines the challenges associated with data acquisition, preprocessing, and annotation, along with strategies to mitigate them. Furthermore, it discusses the integration of multimodal imaging modalities, to improve efficiency and reliability of tumor characterization. The review also surveys benchmark dataset sand various strategies commonly employed in this domain. As a result, propose future directions for advancing the field of bone tumor analysis using deep learning methodologies.

1 Introduction

Bone tumors signify a diverse spectrum of neoplastic diseases that can arise from any bone in the body, ranging from benign lesions to highly malignant tumors. Accurate characterization and classification of these tumors are essential for optimal patient management, including treatment planning, prognosis assessment, and monitoring of therapeutic response. Historically, the analysis of bone tumors has heavily relied on manual analysis of medical images by radiologists and oncologists, which is not only time-consuming but also subject to variability and subjectivity among different

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observers. Moreover, the intricate morphological features of bone tumors, coupled with the variability in imaging modalities pose significant challenges for traditional image analysis methods as shown in fig 1 (A) and (B).

In recent years, the rapid advancements in DL techniques have revolutionized the field of medical image analysis by enabling automated and accurate segmentation and classification of pathological structures. DL, a type of AI based by the architecture and functioning of the human mind, has shown exceptional effectiveness in a diversity of medical imaging claims. Particularly CNNs, have exhibited superior presentation in extracting discriminative features from medical images and making accurate predictions.

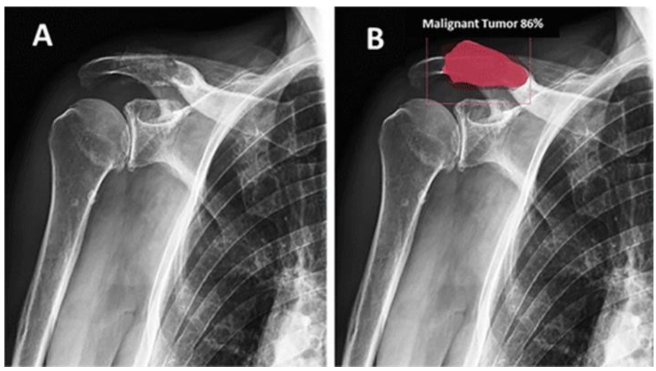

Fig. 1. A Schematic diagram of Bone Tumor Identification (A) Input Image, (B) Segmentation of Tumor.

The use of DL in bone tumor analysis holds immense prospective to overcome the restrictions of traditional image analysis methods and significantly improve diagnostic accuracy and efficiency. However, despite the growing interest and research in this area, there remains a need for a comprehensive review that synthesizes the latest advancements, discusses the challenges and limitations, and outlines future research directions. This paper aims to connect this gap by offering a complete overview of cutting- edge deep learning algorithms for bone tumor segmentation and classification. Through a critical analysis of existing literature, key challenges such as data acquisition, annotation, and validation will be addressed, and potential solutions and future research directions will be discussed. This evaluation aims to provide practical insights, engaged in the variety of bone tumor pathology to be a step forward in custom-made medicine and specific oncology.

2 Challenges

There are ongoing challenges in the use of DL techniques for the analysis of bone tumors. In the context of medical images, so many challenges will be there, among them obtaining or annotating such data is an important question. Although there are more publicly available medical datasets, obtaining diverse, well-annotated data to train DL models remains a challenge. Additionally, the need for preprocessing methods to improve input data quality and the need for uniform annotation protocols across various imaging modalities are other challenges. Moreover, the heterogeneous nature of bone tumor shapes and their inconsistent presentation across individuals result in a challenging segmentation task that requires reliable and sophisticated algorithms to differentiate between tumor boundaries and the surrounding anatomical features or noise. In addition, the multispectral and multimodal aspects of imaging data provide an extra challenge, making advanced fusion methods necessary to boost complementarity of the information extracted. Sustainable improvements in bone tumor analysis using deep learning not only need collaboration between clinicians, medical imaging, and computer scientists; they also rely on promising approaches to deal with these challenges.

3 Background Studies

3.1 Review on Machine Learning Models

Giradkar*et al.,* (2020) investigated the asymptomatic bone stress injuries are clinically significant by the analysis of their frequency, location, and configuration. The current study provides the first data on risk, which is crucial to identifying likely asymptomatic bone stress injuries, and will allow further evaluation studies to reduce the risk of symptomatic bone stress injuries in the future. These findings enhance the clinical guidance and rehabilitation planning of individuals at risk of stress fractures.

Shrivastava*et* al., (2020) explored different methods like powered ML algorithms to study, learn and improve. And machine learning techniques are obviously good at analyzing medical images and finding patterns which can be used to detect abnormality in m structures and features. These improvements in the detection of abnormalities also indicate that the techniques can further assist radiologists and clinicians in bone cancer diagnosis with high accuracy and efficiency.

Sharma *et* al., (2021) utilized the algorithms for edge detection and feature extraction through HOG. Two types of feature sets were prepared and tested for the SVM and RF models: one with and one without HOG. HOG: The feature set with HOG surpassed the feature set without HOG by a large margin. The HOG trained SVM model (f1='0.93') had a better f1-score than the f1-score of 0.77 for the above RF model.

Shukla *et* al., (2020) explored image segmentation techniques including Sobel, Prewitt, Canny, K-means, and Region Growing for detecting osteosarcoma cancer on X- ray images. Experimented with MATLAB-based implementations. Concluded by identifying the best-suited segmentation method for grayscale X-ray images, providing insights for future research directions in bone cancer detection.

Anand *et* al., (2022) proposed a DC-ELM algorithm for cancer type assessment based on histopathology images. Utilized feature extraction and classification using a fusion of classifiers. Demonstrated the effectiveness of the proposed algorithm in differentiating healthy and unhealthy bone regions, offering potential for automated cancer assessment in histopathology images.

Marwa*et* al., (2022) Automatic segmentation of USCT bone images is achieved. First, the VSMN is enhanced for USCT noise reduction and dataset augmentation. The suggested method yields high dissection accurateness for testing with minimal error, beating state-of-the-art methods. It exhibits the capacity to enhance USCT data and autonomously segment bone structures, with high accuracy.

Saranya *et* al., (2022) analyzed fibrous dysplasia (FD) bone images. Various image processing methods, including image filters, segmentation, and edge detection, are engaged.

The proposed method demonstrates high accuracy in segmenting fibrous regions in bone images, showing improvement in segmentation loss with each iteration. The accuracy metrics indicate the effectiveness of the segmentation process.

VonSchacky*et* al., (2022) formulated on various test sets. The best-performance ML model, based on an ANN, achieves excellent accuracy and sensitivity when differentiating among benign and malignant bone lesions. The model outperforms radiology residents and achieves comparable accuracy to specialized radiologists.

Arunachalam *et* al., (2019) developed Multiple ML models are trained and compared for performance. The proposed ML and DL models achieve exceptional performance in classifying tumor regions in osteosarcoma histopathology images, providing a fully automated tumor assessment pipeline.

Lingappa*et* al., (2023) employed for bone cancer type assessment. The proposed method demonstrates extremely accurate results in bone cancer type assessment, outperforming existing methods in terms of accuracy, specificity, and sensitivity.

Phan *et* al., (2024) extracted the Image processing methods are combined for brain and pancreatic tumor identification. Each technique contributes to different stages of image processing. The combined method achieves improved performance in brain and pancreatic tumor identification, enhancing efficiency, precision, and creativity in therapeutic settings.

Papandrianos*et* al., (2020) employed for Whole-body MM bone lesion identification using 68Ga-Pentixa PET/CT images. The models use multimodal data for lesion segmentation and identification. Deep learning methods, particularly W-Net, demonstrate superior performance in lesion segmentation and detection on 68Ga-Pentixafor PET/CT scans, outperforming traditional machine learning methods.

Schnider*et* al., (2020) trained to segment over 100 distinct bones instantaneously in CT scans. It enables robust segmentation of over 100 different bones in CT images, which can help in providing rich semantic information in the stage of diagnosis, planning and navigation for a surgery.

3.2 Review on Deep Learning Models

Singh *et al.,* (2020) utilized CHOG for feature extraction and Extreme Convolutional Deep Learning Machine (ECDLM) for classification. A well-established methodology was used, including preprocessing steps like noise removal, image resize and smoothening which helped improve input data quality. The CHOG features were helpful in enhancing the localization of the anomalous regions as well as the overall accuracy regarding the identification of the tumours.

Do *et al.,* (2020) created an end-to-end detection of knee bone tumors that combines segmentation and classification of tumors through multi-level masks and a feedforward, regularized neural network. The multi-level masks also helped the neural network retain some semantic information surrounding these tumor mixtures and resulted in a better segmentation.

Zhan *et al.,* (2023) proposed the SEAGNET, for a boundary key point selection module and a mixed attention mechanism. In the SEAGNET, the edge attention may be learned by supervising the gap between the edge attention and the boundary key points, thus effectively reserving the fine-grained edge feature information and consequently localizing the malignant tumor lesion more accurately with boundary key points.

Baidyakayal*et al.,* (2020) compared nine segmentation methods such as Otsu thresholding, active contour, and deep feed-forward neural network (DNN) on a DWI dataset for the segmentation of osteosarcoma. The comparative analysis of the segmentation algorithms gave us insights into their strengths and weaknesses which guided us in choosing appropriate algorithms for the segmentation of osteosarcoma. In addition, analysis of ADC in segmented tumor masks demonstrated the ability of DWI to characterize tumors non-invasively.

Anand *et al.,* (2023) adopted classical feature extraction and classification methods on bone cancer histopathological images through deep learning frameworks, improved XGBoost, and Whale optimization. A solid classification of the histopathological images was obtained, and the accurate recognition of bone cancer was possible for the time by using the proposed method consisting of Tsallis Entropy for feature extraction followed by Efficient Net-based CNN for classification. ROI extraction and Whale optimization augmented XGBoost also improved classification performance.

Shouman*et al.,* (2024) proposed a CNN-based technique to classify pelvic bone tumors, using dense net architecture, and provided a training using the CT images and evaluation based on sensitivity, specificity and F1-score. Utilizing DenseNet architecture allowed the automatic extraction of features from CT images to accurately classify pelvic bone tumors. The evaluation metrics included diverse evaluation metrics and could ensure that the model was reliable for clinical diagnosis.

Ponlatha*et al.,* (2022) proposed a DL based approach for detection of bone tumor using histological images, specifically Chondrosarcoma, Ewing sarcoma, and Osteosarcoma. The method also gives an improved accuracy and sensitivity using histological images of various types of bone tumors processed through the convolutional neural networks. Bone tumor type classification helps to the development of customized treatment plan.

Georgeanu*et al.,* (2022) utilized pretrained deep learning classifiers to predict the type of bone tumors from MRI scans using the ResNet50 models and a clinical model for classification. Combining clinical data with deep-learning classifiers facilitates better assessment of tumor malignancy using imaging features and patient-specific characteristics. Since high accuracies are achieved in both training and validation phases, the promising capabilities of this method can assist clinicians to make better diagnostic decisions.

Eweje*et* al., (2021) described a DL algorithm based on MRI images and persistent demographics for the differentiation of benign and malignant bone lesions. The model performed as well as expert radiologists at distinguishing among benign and malignant lesions of bone, suggesting it has potential in assisting clinical diagnosis through reducing inappropriate referrals.

Altameem*et* al., (2020) used intutionistic fuzzy rank correlation in bone images for tumor detection, which is afterwards processed through feature extraction and deep neural networks. Using experiments that were based on MATLAB, we then analyzed the performance of this system. Intuitionistic fuzzy rank correlation-based DNN were used for tumor detection and feature extraction, and the accuracies of the best features obtained were 99.1% for bone cancer prediction, respectively, shortly illustrate the effectiveness of our approach.

Zhou *et* al., (2022) summarized deep learning workflows on medical images and reviewed applications in bone tumor diagnosis and prognosis prediction. Deep learning shows promise in various tasks related to bone tumors, including detection, segmentation, classification, and prognosis prediction, offering potential for improved diagnosis and patient management.

Ye *et* al., (2023) developed an ensemble DL framework for multi-parametric MRI-based detection, segmentation, and classification of primary bone cancers and bone infections. In autonomously identifying, segmenting, and categorizing bone cancers and infections, the ensemble framework outperformed novice radiologists and was similar to senior radiologists.

Gawade*et* al., (2023) proposed supervised DL methods for automated bone cancer detection using user-weighted model selection. Tested various models and evaluated performance metrics. Achieved high accuracy (90.36%) and precision (89.51%) in bone cancer prediction tasks using the selected residual neural network (ResNet101) algorithm.

Paranavithana*et* al., (2023) conducted a systematic review of segmentation approaches for individual among benign and malignant bone lesions and describing malignant bone lesions. Identified neural network-based approaches and CT-based imaging as commonly used methods. Highlighted the need for standardization and clinical translation of segmentation techniques in bone tumor diagnosis.

Do *et* al., (2021) developed A Seg-Unet system for finding and categorizing normal knee bone areas, benign-tumor, or malignant-tumor. Achieved superior performance in knee bone tumor detection compared to other methods, demonstrating potential for assisting physicians in radiographic interpretation.

Hussain *et* al., (2021) explored to discriminate DL models, especially FCNs, outperform conventional segmentation techniques. Accurate femur segmentation improves bone mineral density calculations for osteoporosis diagnosis.

Hsieh *et* al., (2021) applied to increase the effectiveness of bone metastasis identification using bone scans. Simulations based on CNN, including CNNs, ResNet, and DenseNet, are developed and evaluated with contrastive learning. DL algorithms, especially with contrastive learning, demonstrate high accuracy and performance in bone metastasis detection on bone scans. The high negative predictive value indicates potential clinical utility in safely excluding bone metastases.

Li *et* al., (2024) suggested for the automated identification of abnormal images of bone tumors. The model integrates ECA blocks to enhance feature extraction. EENet achieves high accuracy, precision, recall, specificity, and F1-score in bone tumor classification, prominence it's probable as a clinical diagnostic tool.

Sampath *et* al., (2024) employed to categorize normal and cancerous bone images. Pre-processing, segmentation, and classification using CNN models, including AlexNet, are performed. The AlexNet model demonstrates superior performance in accurately classifying normal and cancerous bone images, indicating its potential for early detection of bone cancer.

Xu *et* al., (2018) PET/CT scans with 68Ga-Pentixa were used to detect MM bone lesions across the body. The models use multimodal data for lesion segmentation and identification.

Deep learning methods, particularly W-Net, demonstrate superior performance in lesion segmentation and detection on 68Ga-Pentixafor PET/CT scans, outperforming traditional machine learning methods.

Hussain *et* al., (2018) employed for accurate femur segmentation in DXA imaging. A Pixel Label Decision Tree (PLDT) approach is proposed for feature extraction and selection to improve femur segmentation accuracy. PLDT achieves higher accuracy in femur segmentation compared to conventional segmentation techniques, improving bone mineral density computation for osteoporosis diagnosis.

Isinkaye*et* al., (2021) Applied to bone x-ray images to determine the most effective way for quick medical diagnosis. Active contour model using snake model is employed for bone image segmentation.

4 Problem Statement

Medical imaging is a rapidly changing field that has revolutionized the diagnosis and therapy of a wide range of diseases and conditions, providing both invaluable opportunities and challenges. But there are also some very important hurdles still to be overcome despite much of this progress. A great example of this is identifying anatomical structures within medical images. Introduction Accurate segmentation is critical for tasks such as tumor detection, bone mineral density calculation, and metastasis site determination. Moreover differentiating between malignant and benign bone lesions continues to be a challenging task which requires robust ML models trained on diverse datasets on radiomic characteristics and demographics. In addition, fully automated tools that can accurately locate viable and necrotic regions in histopathology images would also be helpful for assessment of tumor in a much more versatile way, as it has been in osteosarcoma histopathology images, highlighting a strong need for automation. In addition, deep learning algorithms are the key to enhancing detection and classification of bone metastases on functional imaging modalities including bone or PET/CT scans, providing a more reliable diagnosis while alleviating the burden to physicians. In view of these challenges, recent studies, have emerged where deep learning models can tackle these challenges and enhance the effectiveness and accuracy of medical imaging databases. Researchers, therefore, focus on overcoming these challenges to improve clinical decision-making, patient care, and ultimately further advancements in medical imaging technology and healthcare delivery.

5 Conclusions

The current review on studies highlights the breath- taking advances and still unmet needs in the use of ML and DL techniques in medical image analysis. These researches have been demonstrated that by using smart algorithms the diagnostic accuracy can be raised. Treatment planning, and patient care from different clinical territories.

But there are still a number of hurdles to overcome, especially when it comes to accurately segmenting anatomical objects — especially in complicated imaging. Similarly, the accurate classification of benign and malignant bone lesions, is still an active area of development, requiring robust designs and machine learning models trained on heterogeneous datasets.

Also, the demand for a fully automatic tool which accurately detects the tumor regions due to automation of tumor assessment by machine in histopathology images is very challenging.

Research background Bone metastasis is a [common occurrence in advanced cancer and negatively impacts the quality of life and prognosis of patients with cancer. Functional imaging, such as bone scintigraphy, MRI, and PET, can be used for the detection and classification of bone metastases. Although with these challenges, the combined results illustrate how DL models can potentially provide solutions to overcome and improve efficiency and accuracy aspects of medical image analysis.

Towards this, the proposed research is aiming towards the improvement of clinical decision making, patient care, and ultimately improving technology and delivery systems in medical imaging. In summary, by driving discoveries in the field and bringing these advances into the clinic, future research performed by interdisciplinary teams can continue to have significant impact on the lives of patients and providers.

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