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A Recent Survey On Bone Tumor Detection And Classification Using Deep Learning Techniques

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Abstract:
Recent advances in medical imaging with the application of deep learning techniques have already contributed to bone tumor detection and classification and can also offer potentially effective early detection and treatment planning. This review discusses current trends in the use of deep learning on bone tumor analysis in different medical imaging modalities like X-ray, CT, MRI, and Bone scintigraphy. Finally, this paper uncovers the history of detection methods, from machine learning to state-of-the-art deep learning architectures, and evaluates them not only in terms of accuracy but also in terms of performance reliability. The summary of these studies that have been performed by some authors, like automated bone suppression approaches, feature extraction approaches, and domain-specified deep learning approaches for different imaging modalities, are studied in the paper. Some research shows that by making very little progress in the review of convolutional neural networks (CNN) and their extensions, they have made considerable progress in detection and classification tasks to accuracies of greater than 95%. Another area in this paper is the problems involving the absence of datasets and the requirement for a standard evaluation protocol. It provides a review of several datasets that were used in some of the studies, several evaluation techniques, and finally, an evaluation comparison among different deep learning architectures. Furthermore, this study points out the issues with utilizing plain images only and suggests the following areas for future research, namely that both multi-modal fusion approaches and more diverse, comprehensive datasets are needed to generalize better for fast, efficient, and accurate detections.

Key Word: *Convolutional Neural Network, Residual Network, Owl Search Algorithm, Bone Metastasis, Transfer Learning, Medical Imaging.*

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I. Introduction

Early diagnosis is the prediction of the patient outcome of bone tumors [17]. With the fast evolution of deep learning algorithms, advances in medical imaging technologies have enabled much more automatic and precise detection of bone tumor detection and classification. Diagnostic approaches, according to conventional bioinformatics, are always based on the interpretation of the experience of radiologists, taking a lot of time and being susceptible to inter-observer Variability [18]. The coming of the age of deep learning in the analysis of medical images has led to a revolution in the process of bone tumor diagnosis. These algorithms are so advanced that they can automatically extract useful features and learn very complex patterns[8]. While deep learning has already shown spectacular promise in combination with different imaging modalities to increase accuracy and efficiency, the current users were previously incapable of utilizing it due to insufficient databases. As with previous studies, recent advances have been seen in developing deep-learning architectures for bone tumor analysis. Both state-of-the-art CNNs and Convolutional Neural Networks (CNNs) now stand out as the first choice for detection and classification tasks [4]. A number of factors, including (1) an increase in the availability of medical imaging data, (2) an increase in computational power, (3) the development of new deep learning architectures, and (4) the demand for automated diagnosis systems in a clinical environment, have motivated advances in these approaches. Deep learning in bone tumor analysis is applied using different imaging modalities. Automated analysis has been extensively explored in X-ray imaging modality. It also increased the efficacy of CT and MRI studies for bone metastases [5]. As a result, diagnostic accuracy is improved, and interpretation time has been shortened. Additionally, there has been the fusion of multiple imaging modalities, which permitted greater analytical techniques. As an example, studies have shown that combining different imaging modalities through data fusion, such as different imaging modalities, provides additional information that enhances commonality [11]. In cases that involve complex analysis, this multi-modal approach has been popular because analyses based on one modality may not suffice. Manipulation of preprocessing and feature extraction techniques plays an important role in the performance of the model.

Studies have proved that any advanced preprocessing steps combined with feature extraction techniques can vastly improve model performance [7]. Consequently, hybrid approaches have been developed by merging the traditional image processing methods with state-of-the-art deep learning algorithms.

II. Tumor Detection Methods

The history of bone tumor detection methods using deep learning has undergone significant progress over the past few years. The methods can be classified into a number of different approaches, each with its own specific characteristics and uses. There are various studies on Tumor detection methods and hybrid methods performed by several authors. These methods are known for their accuracy in detecting the tumor more accurately compared with traditional methods.

Automated Bone Suppression Techniques: The method proposed by Cardenas et al. [3] is based on improving the contrast of tumors through the suppression of normal bone structures in radiographic images. Their deep convolutional neural network achieves this by learning the common characteristics of healthy bone tissue and cleverly eliminating these features from the image, thereby improving the visibility of abnormal growth. The process has been found extremely effective in detecting faint bone lesions that may otherwise be masked by overlapping bone structures. The process is particularly efficient in chest radiographs, where rib structures frequently overlap with potential tumor locations.

Combination of deep learning and the Owl Search optimization algorithms: Alabdulkreem et al. [1]. The hybrid process makes use of the efficiency of the Owl Search Algorithm in choosing features by employing deep learning techniques for pattern recognition. It is of note that the process allows the model parameters to be modified in an adaptive fashion in order to arrive at optimal performance and thereby improve detection accuracy, especially for faint bone abnormalities.

MRI-based detection: Liu et al. [5] designed an MRI-based detection system that is dedicated to the detection of bone metastases in the pelvic regions in prostate cancer patients. According to their method, they detect regions of interest first with a region proposal network, then perform a more detailed analysis using another classifier. It has been found to be very effective in differentiating between benign and malignant lesions in complicated anatomical targets.

Active Contour with Deep Learning: Lingappa et al. [10] proposed a new combination of active contour methods with deep learning models. The method uses an enhanced mechanism where deep learning-derived features enhance active contour evolution and improve tumor boundary detection accuracy. The use of bagging and boosting methods helps to improve the robustness of the detection process, particularly where the tumor boundaries are unclear.

CT-Based Detection Techniques: Belue et al. [11] focused on the development of a bespoke system to identify bone lesions on CT scans. The method uses a deep learning network architecture that is optimized to identify the three-dimensional aspect of CT data to successfully incorporate spatial context between multiple slices. It is shown that the system is able to detect multiple lesions in a single scan and does so well under a variety of tumor size and shape variations.

III. Tumor Classification Methods

Deep learning-based bone tumor classification has significantly advanced to drive the development of various strategies aimed at tackling multiple aspects of the classification problem.

CNN Architectures for Bone Cancer Classification: Sampath et al. [2] investigated different CNN architectures to attribute the classification of bone cancer to CT scans. They did great work by comparing such architectures as ResNet, DenseNet, and VGGNet and showed that deeper architectures tend to give better performance as deeper architectures are more advantageous than fewer layers of networks.

The ResNet-50 architecture was the best option, as it offered the best balance of computational cost and classification accuracy. The efficacy of their method stems from the network's ability to maintain gradient flow through skip connections, which improves learning from complex bone structures. Their method excelled particularly in discriminating between different bone lesion types with excellent accuracy for early detection.

Gawade et al. [4] designed a customized CNN architecture specifically optimized for osteosarcoma classification. Their method integrated domain knowledge into the network architecture in the form of domain-specific convolutional blocks that identify local and global bone texture patterns. Particular attention mechanisms are used in the design to draw attention to areas of interest in the image, which is very important for the localization of fine differences between tumor grades. In different tissue types and MRI field strengths, their method differentiated different stages of osteosarcoma well and thus offered useful information in planning treatment.

Xception Methods: Bathroom et al. [6] employed the Xception algorithm for the classification of upper bone abnormalities using its depthwise separable convolutions for effective feature extraction. Their design employed bone-specific feature learning customizations, including spatial and textural information essential for tumor classification. The method showed high robustness in cases of variable image qualities and tumor presentations, making it highly beneficial for clinical use. The effectiveness of this method is in its capability to differentiate well between different bone abnormality types and minimize computational complexity.

Feature-Based Machine Learning:

Sharma et al. [7] proposed a hybrid method combining conventional feature extraction methods with sophisticated machine learning models. Their method initially extracts handcrafted features like texture descriptors, shape statistics, and intensity patterns, followed by deep learning for feature selection and classification. This method showed high effectiveness in cases where pure deep learning methods would fail due to limited data availability. The integration of domain knowledge in feature selection, along with neural network learning capabilities, formed a robust classification system.

Transfer Learning Applications: He et al. [13] showed the effectiveness of transfer learning in bone tumor classification, specifically with primary bone tumors in radiographs. Their method used pre-trained networks fine-tuned on bone-specific datasets, showing that knowledge transfer from large-scale image recognition tasks can effectively be applied to medical imaging tasks. The method was especially useful for medical institutions with limited datasets, working well with a lot of accuracy while needing much less training data compared to training from scratch.

IV. Datasets

There are various Tumor datasets in which some are publicly available and rest are private collections. These datasets are widely used in various medical imaging studies. Some studies used clinical imaging collections from various medical institutions. These collections often contain X-ray images [1], CT scans [2], MRI scans [5], and Bone scintigraphy images [9]. The datasets are of varying size and composition. The number of cases ranged from hundreds to thousands of images. The image modalities are single or multiple imaging modalities. The annotation types are bounding boxes, segmentation masks, and classification labels. Patient demographics have varying age groups and conditions. While some studies use publicly available datasets, most use private collections from medical institutions. This is a cause for concern for reproducibility and standardization of results. The quality of annotations varies between datasets. Some of the common issues are the limited size of available datasets, Class imbalance issues, Variability in image quality and acquisition protocols, and lack of standardization in annotation methods.

V. Results

The performance evaluation of deep learning methods in bone tumor detection and classification has demonstrated remarkable progress in various studies. Various detection methods have demonstrated remarkable performance with various imaging modalities. The integration of the Owl Search Algorithm and CNN architecture by Alabdulkreem et al. [1] achieved a remarkable accuracy of 94.5% in X-ray image analysis, with excellent performance in detecting subtle bone abnormalities. This high accuracy can be attributed to the capability of the algorithm to suppress false positives efficiently while maintaining high sensitivity to potential tumor regions. Liu et al. [5] achieved robust performance in MRI-based detection, with 92.8% accuracy in bone metastasis detection, particularly in pelvic regions. Their method achieved remarkable performance in distinguishing between benign and malignant lesions, with a remarkably low false-positive rate. The bone suppression algorithm automatically generated by Cardenas et al. [3] achieved 91.2% accuracy in radiographic analysis, with excellent performance in highlighting subtle bone abnormalities that may be obscured by overlapping structures. The study done by Sampath et al. [2] in the classification field with CT images using various CNN structures (achieving an accuracy of 95.2%) stands out in the field. However, the study showed that deeper networks as a whole fared better until ResNet 50, which showed the best tradeoff between accuracy and computational complexity. It was achieved by Gawade et al. [4] with a custom CNN architecture designed for the detection of osteosarcoma, resulting in an accuracy of 94.8% and a good ability to discriminate between different levels of tumors. The Xception-based method by Barhoom et al. [6] attained 93.1% classification accuracy for upper bone abnormalities, with excellent performance in multi-class classification. Their model performed well even with small training sets and had good feature extraction capability. The feature-based machine learning method by Sharma et al. [7] attained 91.5% accuracy across imaging modalities, emphasizing the need to combine conventional feature extraction techniques with deep learning.

Table no 1: Shows tumor detection results obtained from various studies conducted by authors

Author	Model	Modality	Accuracy
Alabdulkreem et al.	Owl Search Algorithm + CNN	X-RAY	94.5%
Liu et al	Custom CNN	MRI	92.8%
Cardenas et al.	Deep CNN	Radiographic	91.2%
Lingappa et al.	Ensemble Methods	MRI	93.4%

Table no 2 : Shows tumor classification results obtained from various studies conducted by authors

Author	Model	Modality	Accuracy
Sampath et al.	CNN Comparison	CT	95.2%
Gawade et al.	Custom CNN	Multi-Modal	94.8%
Barhoom et al.	Xception	X-RAY	93.1%
Sharma et al.	Feature-based ML	Multi-Modal	91.5%
He et al.	Transfer Learning	Radiographs	90.8%

Key Findings: Performance metrics across the studies revealed some interesting trends. Detection algorithms performed better with X-ray and CT scans than with MRI scans, possibly due to improved standardization and larger datasets available. Classification accuracies were uniformly higher when handling binary classification (benign vs. malignant) than in multi-class cases. Models with attention mechanisms or special architectures for specific tumor types performed better than generic architectures. Transfer learning methods, as used by He et al. [13], reported good performance (90.8% accuracy), especially when handling small dataset sizes. These results must, of course, be considered in the context of their respective size of dataset, class distribution, and, more specifically, their clinical needs. The studies have made direct comparisons of the performance of various samplers difficult because of these variations in both evaluation metrics and characteristics of the datasets.

VI. Conclusion

Deep learning is found to have made outstanding progress in evaluating the comprehensive evaluation of deep learning method for bone tumor detection and classification, however, there is still a lot of room for improvement in the future. The discipline has seen phenomenal advancements in terms of precision and reliability, with detection algorithms achieving up to 94.5% accuracy based on innovative strategies such as the application of the Owl Search Algorithm in conjunction with CNNs [1] and classification algorithms achieving 95.2% accuracy based on advanced CNN architectures [2]. The findings of deep learning portend its potential in changing the bone tumor diagnosis and treatment planning. In particular automated bone suppression techniques [3] and customized frameworks for specialized imaging modalities [5] have been of great help in improving diagnosis ability and making tumor detection more efficient and reliable for different imaging systems. The combination of conventional feature extraction techniques and advanced deep learning methods have proved particularly effective, as evidenced by a number of studies [7, 10], suggesting that hybrid solutions may remain of critical importance in developing the discipline further in the future.

While these advances have been successful, many challenges persist that need to be addressed by the research community. Perhaps the biggest limitation remains the availability of large and diverse datasets, which casts a shadow over models with the need to apply transfer learning and data augmentation techniques in order to achieve robust results. Variability in imaging protocols and annotation schemes across medical institutions also makes standardization of methods harder. The computational expense of deep learning architectures with many layers is also an implementation challenge when working within resource-constrained clinical settings. These limitations indicate a number of promising avenues for future development and research in the field. Multi-modal imaging data fusion is a particularly exciting avenue since distinct imaging modalities are able to provide complementary information about tumor characteristics. Future research should focus on creating architectures that can combine information from X-ray, CT, MRI, and other imaging modalities with special emphasis on real-time object detection models like YOLO for easier and faster detection.

References

[1] Alabdulkreem E, Saeed MK, Alotaibi SS, Allafi R, Mohamed A, Hamza MA. Bone Cancer Detection And Classification Using Owl Search Algorithm With Deep Learning On X-Ray Images. IEEE Access. 2023 Sep 27.

[2] Sampath K, Rajagopal S, Chintanpalli A. A Comparative Analysis Of CNN-Based Deep Learning Architectures For Early Diagnosis Of Bone Cancer Using CT Images. Scientific Reports. 2024 Jan 25;14(1):2144.

[3] Cardenas DA, Ferreira Jr JR, Moreno RA, De Sá Rebelo MD, Krieger JE, Gutierrez MA. Automated Radiographic Bone Suppression With Deep Convolutional Neural Networks. Inmedical Imaging 2021: Biomedical Applications In Molecular, Structural, And Functional Imaging 2021 Feb 15 (Vol. 11600, Pp. 317-323). SPIE.

[4] Gawade S, Bhansali A, Patil K, Shaikh D. Application Of The Convolutional Neural Networks And Supervised Deep-Learning Methods For Osteosarcoma Bone Cancer Detection. Healthcare Analytics. 2023 Nov 1;3:100153.

[5] Liu X, Han C, Cui Y, Xie T, Zhang X, Wang X. Detection And Segmentation Of Pelvic Bones Metastases In MRI Images For Patients With Prostate Cancer Based On Deep Learning. Frontiers In Oncology. 2021 Nov 29;11:773299.

[6] Barhoom AM, Al-Hiealy MR, Abu-Naser SS. Deep Learningxception Algorithm For Upper Bone Abnormalities Classification. Journal Of Theoretical And Applied Information Technology. 2022 Dec 15;100(23):6986-97.

[7] Sharma A, Yadav DP, Garg H, Kumar M, Sharma B, Koundal D. Bone Cancer Detection Using Feature Extraction Based Machine Learning Model. Computational And Mathematical Methods In Medicine. 2021;2021(1):7433186.

[8] Jiang X, Hu Z, Wang S, Zhang Y. Deep Learning For Medical Image-Based Cancer Diagnosis. Cancers. 2023 Jul 13;15(14):3608.

[9] Liu S, Feng M, Qiao T, Cai H, Xu K, Yu X, Jiang W, Lv Z, Wang Y, Li D. Deep Learning For The Automatic Diagnosis And Analysis Of Bone Metastasis On Bone Scintigrams. Cancer Management And Research. 2023 Dec 31:51-65.

[10] Lingappa E, Parvathy LR. Deep Learning-Based Active Contour Technique With Bagging And Boosting Algorithms Hybrid Approach For Detecting Bone Cancer From Mri Scan Images. Multimedia Tools And Applications. 2023 Sep;82(23):36363-77.

[11] Belue MJ, Harmon SA, Yang D, An JY, Gaur S, Law YM, Turkbey E, Xu Z, Tetreault J, Lay NS, Yilmaz EC. Deep Learning-Based Detection And Classification Of Bone Lesions On Staging Computed Tomography In Prostate Cancer: A Development Study. Academic Radiology. 2024 Jan 22.

[12] Eweje FR, Bao B, Wu J, Dalal D, Liao WH, He Y, Luo Y, Lu S, Zhang P, Peng X, Sebro R. Deep Learning For Classification Of Bone Lesions On Routine MRI. Ebiomedicine. 2021 Jun 1;68.

[13] He Y, Pan I, Bao B, Halsey K, Chang M, Liu H, Peng S, Sebro RA, Guan J, Yi T, Delworth AT. Deep Learning-Based Classification Of Primary Bone Tumors On Radiographs: A Preliminary Study. Ebiomedicine. 2020 Dec 1;62.

[14] Dinesh MG, Bacanin N, Askar SS, Abouhawwash M. Diagnostic Ability Of Deep Learning In Detection Of Pancreatic Tumour. Scientific Reports. 2023 Jun 15;13(1):9725.

[15] J. G, M. B. A, M. A. S And R. Munirathinam, "Classification Of Bone Tumor Using Machine Learning And Deep Learning Approach," 2023 7th International Conference On I-SMAC (Iot In Social, Mobile, Analytics And Cloud) (I-SMAC), Kirtipur, Nepal, 2023, Pp. 475-477, Doi: 10.1109/I-SMAC58438.2023.10290254.

[16] Siegel RL, Miller KD, Jemal A. Cancer Statistics, 2019. CA: A Cancer Journal For Clinicians. 2019 Jan;69(1):7-34.

[17] Picci, P. (2020). Epidemiology Of Bone Lesions. In: Picci, P., Et Al. Diagnosis Of Musculoskeletal Tumors And Tumor-Like Conditions. Springer, Cham. Https://Doi.Org/10.1007/978-3-030-29676-6_1

[18] Wyers, M.R. Evaluation Of Pediatric Bone Lesions. Pediatr Radiol 40, 468–473 (2010). Https://Doi.Org/10.1007/S00247-010-1547-4

[19] T. T. Miller, “Bone Tumors And Tumorlike Conditions: Analysis With Conventional Radiography,” Radiology, Vol. 246, No. 3, Pp. 662–674, Mar.2008.

[20] GiJeong Cheon, Min Suk Kim, Jun Ah Lee, Soo-Yong Lee, Wan Hyeong Cho, Won Seok Song, Jae-Soo Koh, Ji Young Yoo, Dong Hyun Oh, Duk Seop Shin, Dae-Geun Jeon, Journal Of Nuclear Medicine Sep 2009, 50 (9) 1435-1440; DOI: 10.2967/Jnumed.109.063602

[21] Hamada, K., Tomita, Y., Inoue, A. Et Al. Evaluation Of Chemotherapy Response In Osteosarcoma With FDG-PET. Ann Nucl Med 23, 89–95 (2009). Https://Doi.Org/10.1007/S12149-008-0213-5

[22] Saifuddin, A. The Accuracy Of Imaging In The Local Staging Of Appendicular Osteosarcoma. Skeletal Radiol 31, 191–201 (2002). Https://Doi.Org/10.1007/S00256-001-0471-Y

[23] Joseph M. Bestic, Daniel E. Wessell, Francesca D. Beaman, R. Carter Cassidy, Gregory J. Czuczman, Jennifer L. Demertzis, Leon Lenchik, Kambiz Motamedi, Jennifer L. Pierce, Akash Sharma, Andrew E. Sloan, Khoi Than, Eric A. Walker, Elizabeth Ying-Kou Yung, Mark J. Kransdorf,, ACR Appropriateness Criteria® Primary Bone Tumors, Journal Of The American College Of Radiology, Volume 17, Issue 5, Supplement, 2020, Pages S226-S238, ISSN 1546-1440, Https://Doi.Org/10.1016/J.Jacr.2020.01.038.

[24] Nascimento, D., Suchard, G., Hatem, M. Et Al. The Role Of Magnetic Resonance Imaging In The Evaluation Of Bone Tumours And Tumour-Like Lesions. Insights Imaging 5, 419–440 (2014). Https://Doi.Org/10.1007/S13244-014-0339-Z

[25] Ojala R, Sequeiros RB, Klemola R, Vahala E, Jyrkinen L, Tervonen O. MR-Guided Bone Biopsy: Preliminary Report Of A New Guiding Method. Journal Of Magnetic Resonance Imaging: An Official Journal Of The International Society For Magnetic Resonance In Medicine. 2002 Jan;15(1):82-6.

[26] Chunli Kong, Linqiang Lai, Xiaofeng Jin, Weiyue Chen, Jiayi Ding, Liyun Zheng, Dengke Zhang, Xihui Ying, Xiaoxiao Chen, Minjiang Chen, Jianfei Tu, Jiansong Ji, Machine Learning Classifier For Preoperative Prediction Of Early Recurrence After Bronchial Arterial Chemoembolization Treatment In Lung Cancer Patients, Academic Radiology, Volume 30, Issue 12, 2023, Pages 2880-2893, ISSN 1076-6332, Https://Doi.Org/10.1016/J.Acra.2023.04.011.

[27] Shao, Junjie, Lingxiao Zhou, Sze Yan Fion Yeung, Ting Lei, Wanlong Zhang, And Xiaocong Yuan. 2023. "Pulmonary Nodule Detection And Classification Using All-Optical Deep Diffractive Neural Network" Life 13, No. 5: 1148. Https://Doi.Org/10.3390/Life13051148

[28] Yinping Chan, Xuan Liu, Tangsheng Wang, Jingjing Dai, Yaoqin Xie, Xiaokun Liang, An Attention-Based Deep Convolutional Neural Network For Ultra-Sparse-View CT Reconstruction, Computers In Biology And Medicine, Volume 161, 2023, 106888, ISSN 0010-4825, Https://Doi.Org/10.1016/J.Compbiomed.2023.106888.

[29] M. S, S. S. Patil, S. D. V, R. K. Reddy And S. K. K N, "A Recent Survey On Bone Cancer Detection Using Deep Learning Techniques," 2024 Second International Conference On Advances In Information Technology (ICAIT), Chikkamagaluru, Karnataka, India, 2024, Pp. 1-6, Doi: 10.1109/ICAIT61638.2024.10690575.

[30] Venkataramana, M., E. Sreenivasa Reddy, C. H. Satyanarayana, And S. Anuradha. "A Review Of Recent Texture Classification: Methods." IOSR Journal Of Computer Engineering (IOSR-JCE) 14, No. 1 (2013): 54-60.