Bone Cancer Detection using Hybrid Machine Learning And Deep Learning: A survey

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Abstract. Bone cancer, predominantly primary bone tumors, is a heterogeneous group of malignant neoplasms that originate in the skeletal system. Bone cancer is an oncological disease that affects bone cells and is characterized by some abnormal cells in the bone tissue begin to grow uncontrollably forming malignant neoplasms. Even though this type of disease is rare, such tumors represent a significant diagnostic and therapeutic challenge due to their diversity and the similarity of many of their symptoms to signs of other bone diseases, such as infections . In the United States, this type of tumor is the third leading cause of cancer death in individuals younger than twenty years. The main types of primary bone cancer include: osteosarcoma, chondrosarcoma, Ewing sarcoma Medical imaging techniques such asX-rays, MRI, computed tomography, and biopsy is performed for diagnosis. Early diagnosis significantly increases the chances of successful treatment and long-term remission . This survey presents a comprehensive systematic review of studies and research conducted in the domain of machine learning approaches, deep learning algorithms, the utilization of optimization algorithms for bone cancer detection and classification. Deep learning (DL), a branch of artificial intelligence, has emerged as an effective tool for analyzing medical images and classifying diseases. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated an exceptional ability to automatically extract hierarchical features from medical images, enabling the accurate detection and classification of bone tumors. These models can learn complex patterns and subtle variations in imaging data that may be difficult for human observers to discern, thus enhancing diagnostic accuracy and efficiency

Keywords: Bone Cancer , Deep Learning, Machine Learning , X-ray dataset , Optimization

1 Introduction

Bone cancer is a devastating and potentially fatal disease. Manual methods are time-consuming and expertise-dependent. Thus, it is crucial to have an automatic system that classifies and differentiates cancerous bone from normal bone. Presumably, the only element that can increase a cancer patient's survival probability is early detection in its

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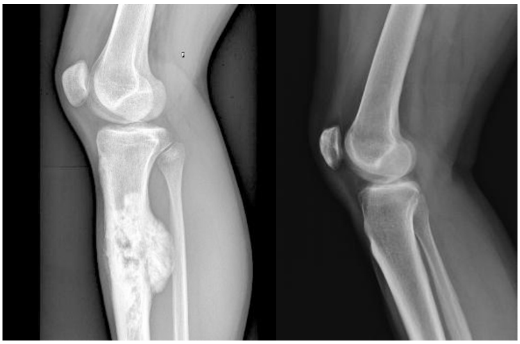
initial stage . [1] Currently, the time required to diagnose bone cancer may extend to several months as a result of being prone to late detection, and it would be advantageous if methods were developed that can help improve the accuracy of early disease detection . Medical imaging techniques such as X-rays, MRI, computed tomography, and biopsy are performed for diagnosis. The rapid development of computer technologies in recent years and the popularization of artificial intelligence have led to the development of machine learning and deep learning programs that make it possible to perform analysis of medical imaging and predict various diseases. By learning complex patterns from medical data, many of the imaging algorithms are trained on radiologic and histopathological images to recognize subtle signs of bone cancer not detectable to the human eye and hence improve diagnostic performance and reduce the chance of misdiagnosis. The potential of these new approaches in the field of bone cancer is significant for the future development of early detection and effective treatment planning. [2]

The combination of AI with imaging and biological data presents a powerful platform for advancing early diagnosis, individualized therapy, and prognostic evaluation in patients with osteosarcoma. Machine learning (ML), as a sub-paradigm of artificial intelligence, has become an effective instrument for constructing predictive models from large-scale datasets Machine learning algorithms have been successfully applied in biomedical research, enabling the identification of biomarkers and therapeutic targets. [3]

This survey also includes recent studies discussing the applications of CNNs, Vision Transformers (ViTs), and data fusion techniques in bone cancer detection. First, the researcher provides a critical analysis of the methodologies used by authors in this domain and the research done on the subject, presenting their reported precision, accuracy, recall, and F1-score results . The strengths and limitations of advanced algorithms are also discussed.



Bone cancer normal

Fig. 1. :Bone cancer and normal bone

This survey is organized into following sections, section II, and section III describes literature reviews of what the researchers presented to detect bone cancer using machine learning , deep learning, respectively, while section IV describes and includes literature reviews bone cancer detection using hybrid Deep Learning . Section V, presented discusses the related works.VI, presented future work, lastly, the conclusion are presented in Section VII.

2 bone Cancer Detection using Machine Learning

Machine learning (ML) has emerged as a promising approach to enhancing the accuracy and efficiency of diagnosis in medical imaging. ML algorithms can analyze massive amounts of imaging and clinical data, learn complex patterns, and distinguish between benign and malignant bone lesions with high precision. This section reviews classification methodsfor detection of Bone Cancer Using Machine Learning and Imaging Techniques , as described in Table 1 :

Sharma et al. [1] automated bone cancer classification system to Bone Cancer Detection Using Feature Extraction . proposes an automated bone cancer classification system using image preprocessing (median filter and sharpening), segmentation (Canny edge detection), and feature extraction (texture descriptors with and without Histogram of Oriented Gradients - HOG). bone tumors were classified into malignant and benign categories , Two machine learning models, Support Vector Machine(SVM) and Random Forest, were trained and compared to identify cancerous versus healthy bone , The authors conducted two experiments, one using HOG feature sets and another without HOG features. SVM and HOG features achieved 92.5% accuracy . Sun et al. [2] developed ML models to differentiate benign from malignant bone lesions, they applied LASSO (Least Absolute Shrinkage and Selection Operator) logistic regression for feature selection and model building. Although their approach did not explicitly integrate DL, the model was limited by a small dataset and lack of generalizability Their model achieved 91.7% accuracy .

Chen et al. in [3]] have proposed A machine-learning model to predict patient prognosis with Ewing's Sarcoma .They performed a System/Method Retrospective Review using SEER database., four machine learning models were compared Random Forest, Boosted Decision Tree, Support Vector Machine and Neural Network. The model lacked external validation , missing variables in SEER (e.g., surgical margin), data imputation required , Their model archived 86% accuracy . Lingappa et al. in [4] have proposed Artificial Neural Network (ANN) to bone cancer detection using MRI images The proposed system integrates preprocessing, edge detection, morphological operations, segmentation, and feature extraction, followed by classification using an Artificial Neural Network (ANN) to distinguish between normal and malignant cases. MRI images were employed as the primary dataset owing to their high resolution and diagnostic reliability. Performance was evaluated using detection rate and false positive rate, where the ICA–SVMCS approach achieved the best results with a detection rate of 99.25% and reduced false positives compared to other models. Overall, the method demonstrated improved accuracy and robustness, offering a more reliable solution for bone cancer diagnosis than traditional approaches .

Gitto et al. [5] presented an MRI radiomics-based machine learning method to differentiate atypical cartilaginous tumours from grade II chondrosarcomas of long bones , After feature-selection (LASSO + RFE) and class balancing (SMOTE on the training set) they trained an Extra Trees Classifier (an ensemble tree-based method similar to a random forest but with extra randomization) as the final machine learning model in this study specifically using an Extra Trees classifier they used an Extra Trees Classifier,Radiomic feature extraction To ensure the model's robustness, features were selected using stability testing, variance and correlation analysis, and iterative deletion to retain the most informative predictions. The selected features were then used to train and validate a machine learning classifier (e.g., a random forest method or a cluster method , The study was retrospective, used data from two centers, and included an imbalanced dataset The model achieved 92% accuracy .

Thakkar et al. [6] proposed a machine learning (ML)-based framework for faster bone cancer diagnosis . the authors proposed a machine learning based system that integrates both traditional classifiers (SVM, Random Forest, k-NN with hand-crafted features) and deep learning models (VGG16, InceptionV3, ResNet50 with transfer learning) for automated analysis of bone X-ray and MRI images , the study was limited by a small dataset and the exclusion of other respiratory diseases, the other respiratory diseases are not considered ,Results showed that ResNet50 achieved the best performance with 92% accuracy. Zhao et al. [7] proposed a machine learning model for predicting osteosarcoma outcomes The researchers developed a Machine Learning Derived Prognostic Signature (MLDPS) by integrating 66 combinations of 10 ML algorithms. The optimal model was constructed using combinations of, LASSO (Least Absolute Shrinkage and Selection Operator) Random Survival Forest (RSF), Its clinical application is limited by reliance on retrospective datasets, small cohort sizes, and lack of real-world clinical validation. The model achieved 86.6% accuracy

Table 1. An Overview of Existing Studies of bone cancer detection using machine learning

Ref. & Year	Dataset	Dataset Type	ML	Methods	Accuracy
[1] Sharma et al., 2021	X-ray dataset (DICOM images)	X-ray	SVM &RF	Feature extraction + SVM / RF	92.5%
[2] Sun et al., 2021	Medical imaging dataset (X ray, MRI)	X-ray / MRI	SVM RF ResNet50	Traditional ML (SVM, RF) + DL (ResNet50 etc.)	85%
[3] Chen et al., 2021	SEER (Ewing sarcoma cases, n=2332)	Clinical / survival data	ANN	(RF), Boosted (BDT), and (SVM)	86%

[4] Lingappa & Parvathy, 2022	General MRI scans (research datasets)	MRI	ANN	ICA–SSVM–CS	99.25%
[5]Gitto et al ,2022	Long-bone cartilaginous tumour MRI dataset	MRI	LASSO + RFE	LASSO	92%
[6] Thakkar et al., 2025	Medical imaging dataset (X-ray, MRI)	X-ray / MRI	Traditional ML (SVM, RF) + DL (ResNet50 etc.)	(SVM, Random) and (VGG16, InceptionV3, ResNet50)	85%
[7] Zhao et al., 2025	Multiple gene expression datasets (TARGET, GSE etc.)	Genomic (gene expression)	LASSO + RFE	combinations, LASSO + RSF	86.6%

3 Bone cancer detection using deep learning :

Deep learning has revolutionized bone cancer detection by providing comprehensive models capable of automatically extracting features from raw imaging data. Convolutional neural networks (CNNs), artificial neural networks (ANNs), and hybrid architectures have been widely used in various imaging modalities, including computed tomography (CT), magnetic resonance imaging (MRI), x-rays, and histology. as describe in table 2:

He et al. (2020) proposed Deep learning based CNN model to bone cancer detection they used the EfficientNet-B0 convolutional neural network for multi-class classification of primary bone tumors on radiographs. The system was designed to perform both binary classification (benign vs. not-benign, malignant vs. not-malignant) and three-way classification (benign, intermediate, malignant), and its performance was compared with radiologists of varying experience levels Results showed strong performance in binary classification. the study was limited by reliance on retrospective data, variability in imaging protocols across institutions, and lack of integration with multi-modal imaging (e.g., CT, MRI). Their model achieved 87.7% accuracy [8] .

Vandana & Alva (2021) suggest Deep learning-based CNN model to bone cancer detection The approach incorporates image augmentation to expand the dataset and leverages CNN layers (convolution, pooling, fully connected, and softmax for feature extraction and classification of bone histopathology images into malignant, benign, and suggested a deep learning-based CNN model due to morphological abnormalities, a relatively small original dataset, and the need for larger-scale standardized datasets to ensure model generalization and robustness in clinical applications Their model achieved 92.11 % accuracy [9],Tao et al.(2021) suggest Deep learning based CNN model to bone cancer detection they used (VGG-16, InceptionV3), (CNNs) using whole-slide imaging (WSI) to classify bone tumors histopathologically into benign intermediate and malignant categories aiming to reduce subjectivity and improve accuracy, the study was limited by dataset size and lack of external validation. Broader multicentre datasets are needed to confirm the generalizability and clinical applicability of the proposed system, Results showed that VGG-16 and InceptionV3 achieved the best performance with 96.2% accuracy [10] .

von Schacky et al. (2021) suggest Deep learning-based CNN model to bone cancer detection they used a multitask deep learning framework capable of simultaneous bounding box placement, segmentation, and classification of primary bone tumors on radiographs. This approach aimed to enhance diagnostic efficiency and accuracy compared with radiologists, the study limited because only histologically proven bone tumors were included, thus inferring selection bias. and no normal cases were included Their model achieved 80.2% accuracy [11] .

Consalvo et al., 2022 proposed a Deep learning model to Detection and Differentiation of Ewing Sarcoma and Acute Osteomyelitis they used ResNet-18 A two-phase supervised deep learning model dataset was small and imbalanced, limiting generalizability but larger, multi-center datasets are necessary for robust clinical implementation. Their model achieved 94.4% accuracy [12] .

Alabdulkreem et al. (2023) proposed Deep learning model to bone cancer detection they used Owl Search Algorithm with a Deep Learning-Driven Bone Cancer Detection and Classification (OSADL-BCDC) and used a Data augmentation for better dataset generalization. Inception v3 as a feature extractor (no need for manual segmentation),Owl Search Algorithm (OSA) for hyperparameter optimization. ,LSTM as the classifier for detecting and classifying bone cancer, the dataset size and lack of clinical validation limit the generalizability of results for real-world medical applications. Their model achieved 95 % accuracy [13] .

Ho et al., (2023) have proposed a Deep learning (DL) framework to Necrosis ratio assessment in osteosarcoma. They have used A deep learning pipeline using Deep Multi-Magnification Network (DMMN) for pixel-wise segmentation of Hematoxylin & Eosin (H&E) whole-slide images (WSIs) H&E WSIs, to objectively calculate necrosis ratio and predict patient outcomes. Multi-institutional datasets and cell-level annotations are needed for further improvement. They found that the model achieved 90% accuracy [14].

Meem & Hasan, (2023) proposed Deep learning-based CNN model to bone cancer detection The authors proposed using four different pre-trained transfer learning (TL) models EfficientNetB7, InceptionResNetV2 , NasNetLarge, and ResNet50 Transfer learning is a suitable approach because it doesn't require training models from scratch and can work effectively with small datasets. These models were pre-trained on the ImageNet database and fine-tuned for the specific task of osteosarcoma detection using a dataset of H&E-stained histopathology images,Their model achieved 93.29% accuracy [15] .

Vezakis et al., (2023 suggested a hybrid deep learning model integrated with Vision Transformers to Medical Image Analysis and Histopathology Classification to Bone cancer diagnosis The authors conducted a comparative study of multiple deep learning architectures (MobileNetV2, EfficientNet, Residual Networks (ResNet) , Visual Geometry Group Network (VGG) , Vision Transformer, etc.) for classifying histopathological images of osteosarcoma into three categories : Non-Tumor (NT) , Viable Tumor (VT) And Necrosis (NC) the model was limited by The authors recommendedfurther work using regularization, dropout, dimensionality reduction, and pretraining on related datasets to improve generalization They authors recommend further work using regularization, dropout, dimensionality reduction, and pretraining on related datasets to improve generalization , Their model achieved 91% accuracy [16] . Song, L.,et al. in [17 proposed a Primary Bone Tumor Classification Transformer Network (PBTC-TransNet) for accurately classifying primary bone tumors .They have used a PBTC-TransNet, designed to integrate incomplete multimodal images (X-ray, CT, MRI) with patients' clinical characteristics .The model leveraged a flexible fusion strategy that allows robust classification even when some imaging modalities are missing , the model need for further optimization and larger, multi-center validation to enhance its generalizability They have found that PBTC-TransNet achieved 84.3% accuracy .

Sampath et al. (2024) proposed Deep learning-based CNN model to bone cancer detection they used Computer-Aided Diagnosis (CAD) system to utilize image processing techniques and deep learning-based Convolution neural network (CNN) to classify normal and cancerous bone images. They used image processing (median filter, K-means clustering, Canny edge detection) and deep learning with CNN models to classify normal vs. cancerous CT bone images Results revealed that AlexNet model showed a better performance reported best the study was limited by restricted generalizability Further validation with larger and more diverse clinical datasets is required to ensure robustness in real-world applications. Their model achieved 98.18 % accuracy [18].

Wang et al. in [19] have proposed deep learning combined with vision transform to bone cancer detection they used an ensemble deep learning frameworkthat integrates multicenter radiographs with extensive clinical features, comparing its performance against imaging-only models based on EfficientNet-B3, EfficientNet-B4, Vision Transformer, and Swin Transformer. The study was limited by reliance on multicenter retrospective data, challenges in model interpretability, and the need for further validation in broader clinical settings to ensure generalizability, Their model achieved 94.8% accuracy .

Yamana et al., proposed a CNN-based object detection framework integrated with Vision Transformers to Detecting and classifying bone tumours in full-field limb radiographs. The study proposed a transformer-based object detection model (DINO) Detection with transformers with Improved deNoising anchOr boxes) to automatically detect and classify benign versus malignant bone tumours, and compared it with YOLO(You Only Look Once) and human experts , the study was limited by small sample size, focus on limb radiographs only, and exclusion of non-tumour conditions, which restricts generalizability and necessitates further validation before routine clinical adoption. Their model achieved 77% accuracy [20] .

Borji et al., (2025)in [21] suggested a hybrid deep learning model to osteosarcoma detection and classification They have used A hybrid deep learning model combining Convolutional Neural Networks (CNN) for local feature extraction and Vision Transformers (ViT) for global feature representation. Features are concatenated and classified using a Multi-Layer Perceptron (MLP) into four classes: non-tumor (NT), non-viable tumor (NVT), viable tumor (VT), and non-viable ratio (NVR), the study was limited by lack of external validation across multi-institutional datasets limited clinical generalizability They found that the Hybrid CNN and ViT model achieved 99.08% accuracy.Vora et al (2025) The study proposed an intelligent deep learning–based system for automated bone cancer detection and bone age assessment , they used CNN architectures such as InceptionResNetV2, DenseNet201, EfficientNetB0, and Xception, were fine-tuned using transfer learning to perform both classification and regression tasks. The study relies entirely on a single pediatric X-ray dataset, limiting its generalizability across hospitals and imaging types they found that the model 98.21% accuracy [22]

Table 2. An Overview of Existing Studies of bone cancer detection using deep learning.

Ref. & Year	Dataset	Dataset Type	DL	Methods	Accuracy
[8] He et al., 2020	Multi-institutional radiographs	X-ray	CNN	EfficientNet-B0	87.7%
[9] Vandana & Alva, 2021	Collected from Indian hospitals (Kidwai, Kasturba, KVG)	Histopathology	CNN	CNN	92.11%
[10] Tao et al., 2021	Whole-slide images (WSI) of bone tumours	Histopathology (WSI)	CNN	(VGG-16, InceptionV3)	96.2%
[11] von Schacky et al., 2021	Radiographs from Technical University Munich (934 radiographs)	X-ray (radiographs)	CNN	COCO–pretrained Mask R-CNN	80.2%
[12] Consalvo et al., 2022	Pediatric radiographs (182 images, 58 patients)	X-ray	Deep learning	ResNet-18	94.4%
[13] Alabdulkreem et al., 2023	HCT / cytomorphological representation	X-ray / cytology	Deep learning	(OSADL-BCDC)	95%
[14] Ho et al., 2023	Osteosarcoma WSIs	Histopathology	Deep learning	(DMMN)	90%
[15] Meem & Hasan, 2023	Osteosarcoma H&E dataset (UT Southwestern/UT Dallas)	Histopathology	CNNs	(EfficientNetB7, InceptionResNetV2, NasNetLarge, ResNet50)	93.29%
[16] Vezakis et al., 2023	Public osteosarcoma histopathology tiles	Histopathology (tiles)	CNN	MobileNetV2, EfficientNet, ResNet, VGG, ViT	91%
[17] Song et al., 2024	Internal multimodal (X-ray, CT, MRI)	X-ray / CT / MRI	CNN	Transformer-based fusion model, PBTC-TransNet	84.3%
[18] Sampath et al., 2024	Collected from Radiopaedia & TCIA (1141 CT images)	CT	CNN	(CAD) and (AlexNet reported best)	98.18%

[19] Wang et al., 2025	Multicenter radiographs (internal)	X-ray (multicenter)	CNN + ViT	ensemble deep learning framework	94.8%
[20] Yamana et al., 2025	Multi-center limb radiographs	X-ray	CNN & ViT	DINO and YOLO-v8x	77%
[21] Borji et al., 2025	TCIA Osteosarcoma Tumor Assessment (1,144 images)	Histopathology (H&E tiles)	CNN& ViT	(convolutions + pooling + LeakyReLU) (patch embedding + GELU)	99.08%
[22] Vora et al (2025)	GRAZPEDWRI-DX	X-ray	multiple deep learning models	InceptionResNetV2, DenseNet201, EfficientNetB0, and Xception	98.21%

4 Bone cancer detection using Hybrid Machine learning deep learning :

Hybrid approaches that integrate machine learning and deep learning methodologies have emerged as particularly effective tools for detecting bone cancer due to their ability to combine the interpretability and robustness of traditional machine learning algorithms with the feature-learning and abstraction capabilities of deep learning networks. as describe in Table 3 :

von Schacky et al. (2022) applied Machine learning model based on Artificial neural network (ANN) to distinguish between benign and malignant bone they used an ANN combining radiomic and demographic features (age, sex, tumor location) Their model achieved Phase1 acc 94.4%, Phase2 acc 90.3%. the dataset was small, imbalanced, and limited generalizability [22]. Yan et al. (2022) suggested a machine learning model combined with deep learning to bone cancer detection they used compared multiple survival prediction models, including DeepSurv, Neural Multi-Task Logistic Regression (N-MTLR), and Random Survival Forest (RSF), against the traditional CoxPH model , They used the SEER dataset model achieved 90.7 % accuracy , the paper is limited by the retrospective design, reliance on SEER data without external validation, and lack of treatment-specific and molecular/genomic variables [23]. Georgeanu et al. (2022)) proposed Deep learning based using CNN (Convolutional Neural Network) to predict the malignancy of a bone tumour from magnetic resonance imaging (MRI) They used two pretrained ResNet50 models for classifying combined with a feed-forward neural network clinical model that integrates demographic and clinical data. The method removes the need for manual segmentation and enables automated malignancy prediction, the study was limited by its small cohort size (23 patients, 39 scans) and class imbalance, which reduced generalizability ,Their model achieved 95 % accuracy [24] . Anand et al., (2022) proposed Deep Learning (DL) model to Detect Bone Cancer From Histopathological Images They have used Deep Convolutional Extreme Learning Machine (DC-ELM) framework that integrates feature extraction (using Karhunen–Loeve transform), edge detection (Prewitt operator), and an ensemble of classifiers

(SVM, Logistic Regression, Naïve Bayes, KNN, Decision Tree). A stack-based voting mechanism was used to improve classification of histopathology images into different bone cancer categories, the study was limited by relatively small datasets (1,144 tiles) and reliance on ensemble methods rather than fully end-to-end deep learning. Their model achieved 97.27% accuracy [25].walid et al ,2023 in [26] proposed hybrid machine and deep learning model Adapted Deep Ensemble Learning-Based Voting Classifier (ENL-CNE) designed to accurately classify osteosarcoma histopathology images they used a custom CNN model and an adapted heterogeneous ensemble learning-based voting classifier (ENL-CNE) that integrates the custom CNN with fine-tuned NasNetMobile and EfficientNetV2B0 models. Data augmentation and balancing using the Albumentations library were applied to address class imbalance , the model was limited by reliance on a single publicly available dataset with a limited number of images which may restrict model generalizability , they found (ENL-CNE) model achieved 95.63% accuracy . Aarthy et al. in [27] have proposed a four-phase framework combining machine and deep learning to detect bone cancer, they used Median Image Filter (MIF) and Bilateral Filter (BF) to noise removing , Scaled Region Edge Detector (SRED) to edge detection and Screen Cluster Area Segmentation (SCAS) with Relative Scalar Color Histogram (RSCH) to segmentation . they used a Gated CNN (GCNN) with Maximum Standard External Regions (MSER) to Feature Extraction and Classification , they used Small dataset (1114 images).Limited to osteosarcoma (which may lead to poor generalization).they found the model achieved 80% accuracy .Deng et al.(2024) proposed a deep learning-based DCNN model to Diagnosing primary bone tumors The study proposed a deep convolutional neural network (DCNN) model (ResNet34) integrated with imaging omics analysis and a gene expression screening method to support the auxiliary diagnosis of primary bone tumors small sample size and tumor heterogeneity. The study requires larger datasets and optimized algorithms before reliable clinical application Their model achieved 99.8% accuracy [28] . Al-Quraishi et al .(2024) in [29] introduces a hybrid diagnostic framework that integrates deep learning feature extraction with traditional machine learning classifiers to improve osteosarcoma tissue viability prediction they used pre-trained Convolutional Neural Networks (CNNs) used as feature extractors. The authors employed several well-known CNN architectures VGG16, ResNet50, and InceptionV3 using transfer learning to extract deep, high-level image representations from osteosarcoma histopathological slides. The authors trained multiple ML algorithms, including Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting (GB), and Decision Tree (DT) , the model it relies on a single publicly available histopathology dataset , which restricts the model's ability to generalize to diverse imaging conditions and clinical populations and found that the Hybrid Deep Feature Machine Learning Ensemble Voting Classifier Achieved 98.6% accuracy . Dalai et al. (2025) proposed Deep learning based CNN model to bone cancer detection they used Golden Search Optimization with Deep Learning Enabled Computer-Aided Diagnosis for Bone Cancer Classification (GSODL-CADBCC) on X-ray images. The method applies bilateral filtering (BF)for noise removal, uses SqueezeNet for feature extraction, optimizes hyperparameters with the Golden Search Optimization (GSO) algorithm, and classifies features using Improved Cuckoo Search (ICS) combined with LSTM , the study was limited by the restricted availability of external datasets. Broader validation across diverse populations and institutions is necessary for greater generalizability The GSODL-CADBCC achieved 95.52% accuracy [30] . M. Venkata et al (2025) in [30] This study presents a sophisticated framework combining radiology and machine learning for detecting and classifying bone lesions. It utilizes standardized preprocessing, segmentation, and manually designed radiographic feature extraction, followed by dimensionality reduction to retain the most important predictors. Several machine learning classifiers, including support vector machines, random forests, stepwise reinforcement, and logistic regression, and used deep learning framework Intelligent Learning-Based Bone Cancer Detection (IBCDNet) The study is limited by the small size of its single-center dataset, which may reduce the model's generalizability. And they found ILB-BCD model achieved 98.39% accuracy . Venkata Ramana et al. (2025) proposed Deep learning model to bone cancer detection they used (Intelligent Bone Cancer Detection Network) IBCDNet, enhanced with the Intelligent Learning-Based Bone Cancer Detection (ILB-BCD) algorithm The framework integrates advanced concepts like attention mechanisms and residual connections to extract robust features, handle imbalanced data, and improve classification accuracy , their model was trained on a single dataset and thus may not generalize to additional datasets or imaging tools without further validation Their model achieved 98.39 % accuracy [31]

Table 3. An Overview of Existing Studies of bone cancer detection using deep learning and machine learning.

Ref. & Year	Dataset	Dataset Type	ML&DL	Methods	Accuracy
[23] von Schacky et al., 2022	Internal X-ray radiomics dataset (880 patients)	X-ray	ANN	combining radiomic + demographic features (age, sex, tumor location)	90%
[24] Yan et al., 2022	SEER (chondrosarcoma cases)	Clinical records / survival data	ML&DL	DeepSurv, Neural Multi-Task Logistic Regression (N-MTLR),and (RSF)	90.7%
[25] Georgeanu et al., 2022	Small MRI	MRI	CNN	ResNet50	95%
[26] Anand et al., 2022	Two public histopathology bone cancer DBs (tiles)	Histopathology	DC-ELM	ELM + ensemble (SVM, LR, NB, KNN, DT)	97.27%
[27] walid et al ,2023	Osteosarcoma Dataset from UT Southwestern/UT Dallas.	Histopathology	(ENL-CNE)	EfficientNetV2B0 and NasNetMobile with ensemble voting mechanism , (ENL-CNE)	95.63%

[28] Aarthy et al., 2024	Osteosarcoma-Tumor-Assessment (TCIA)	Histopathology (H&E)	CNN	Gated CNN (GCNN) with Maximum Standard External Regions (MSER)	80%
[29] Deng et al. 2024	Retrospective X-ray dataset (130 images)	X-ray	DCNN	deep convolutional neural network (DCNN) model (ResNet34)	99.8%
[30] Al-Quraishi et al .(2024)	Osteosarcoma Histopathology Image	Histopathology (H&E)	CNN	CNN architectures VGG16, ResNet50, and InceptionV3 with (SVM,RF,GB,DT)	98.6%
[31] Dalai et al., 2025	Medical X-ray datasets (various)	X-ray	(GSODL-CADBCC)	(GSODL-CADBCC)	95.52%
[32] Venkata et al (2025)	Osteosarcoma Tumor Assessment	X-ray	ILB-BCD	ML(SVM,RF,GB, DT) with DL (IBCDNet)	98.39%

5 Discussion

This research reviews recent bone cancer detection experimental studies conducted in the fields of ML, DL, Hybrid Models and models improved by MHA Multiple cross-disciplinary data modalities have been explored in this field: histopathological slides, radiological images (X-ray, CT, MRI), genomic data, and patient records each possessing unique strengths and limitations. Histopathology offers high resolution but is data intensive, radiology is effective in revealing structural details but is very sensitive to imaging noise and genomic/clinical data is strong in prognosis but feature selection remains critical . The studied bone cancer cases mostly used different Datasets, such as Osteosarcoma WSIs, SEER, MSKCC osteosarcoma cases and TCIA Osteosarcoma Tumor Assessment. DL models, especially CNNs and Transformers, have achieved high accuracy in tumor classification and segmentation Despite these advances, several challenges remain , such as overfitting and computational costs are often high . To overcome these drawbacks, DL models are often combined with metaheuristic algorithms like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO) as well as network weights regularization weight optimization and feature selection Studies [10], [11], [24], and [29] all confirm that hybrid Models, in which DL does feature extraction and MHAs run optimization mainly, demonstrate strong generalization performance . Even in some cases where the data set size is just 10 to 70 examples accuracy rates ranging from 90%-100% can be using these approaches. Nevertheless, challenges remain to be solved. There is limited diversity in the data sets used, and whether the results can be applied across institutions is still questionable. Furthermore, clinicians require explainable AI methods so clinical trust can be built.

5.1 Critical Analysis of Existing Studies

The literature reviewed shows a significant transition from classical machine learning methods towards deep learning approaches and hybrid intelligent models in bone cancer detection and classification. It has become common to do machine learning–based methods, relying on handcrafted feature extraction mechanisms alongside classifiers such as Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Networks (ANN), and ensemble learning models.

However, even though these approaches performed quite well in several studies, their effectiveness depended significantly on the quality of preprocessing, feature engineering strategies, and dataset characteristics. For instance, Sharma et al. [1], using texture descriptors and SVM and Random Forest classifiers, reached 92.5% classification accuracy. Similarly, Gitto et al. [5] used radiomics-based machine learning with feature selection techniques and achieved 92% accuracy in cartilaginous tumor differentiation. Most traditional ML models, however, have poor feature representation capability and are less resilient to challenging tumor heterogeneity and large medical imaging datasets. Deep learning-based computer-aided systems have improved the performance of recent advances in deep learning. For image classification in imaging, convolutional neural networks (CNNs) possessed great potential to automatically extract hierarchical and discriminative features directly from medical images without having to manually engineer features.

The CNN-based architectures—EfficientNet, ResNet, VGG, InceptionV3, and DenseNet—performed very well in different imaging modalities including X-ray, MRI, CT and histopathological images. Tao et al. [10] achieved 96.2% accuracy of CNN-based whole-slide image classification whereas Sampath et al. [18] attained 98.18% accuracy in CT image classification by AlexNet. Moreover, transfer learning strategies have dramatically increased performance in low-dataset studies using pretrained ImageNet models, as shown by Meem and Hasan [15]. Transformer-based architectures and Vision Transformers (ViTs) are recently seen as promising alternatives for bone tumor analysis, in addition to CNN-based methods, when it comes to modeling long-range dependencies and global contextual relationships in the context of medical images.

Studies such as Wang et al. [19] and Borji et al. [21], showed that hybrid CNN–Transformer architectures outperform conventional CNNs on a number of classification tasks. Specifically, the proposed hybrid CNN–ViT framework proposed by Borji et al. showed a 99.08% accuracy that can be attributed to this dual advantage of local feature extraction features of CNN with the global representation learning ability of Transformers [21]. Based on the reviewed works, the authors identify another trend in these studies is the tendency to hybrid intelligent systems based on deep learning frameworks, with machine learning classifiers, optimization algorithms, and ensemble learning strategies. By and large, these mixed methods proved to be more robust, optimized parameters, and improved in terms of classification performance than single models.

Al-Quraishi et al. [30] employed deep learning feature extraction and conventional classifiers of machine learning (SVM, Random Forest) with 98.6% accuracy. Additionally, other optimization-driven frameworks like OSADL-BCDC [13] and GSODL-CADBCC [31] incorporated metaheuristic optimization methods for hyperparameter tuning and feature optimization for the performance with improved diagnostic performance and stable classification. While the reports in the literature have demonstrated promising progress, some critical limitations remain.

Several previous studies depend on single institutions' relatively small and imbalanced datasets which limits model generalizability and increases the amount of overfitting; this means the data are small and untested by some of the existing studies. Moreover, a sizable number of studies used retrospective data that were not externally validated or were not clinically prospectively validated. Additionally, heterogeneity in imaging procedures, quality of annotation, and tumor variation makes model generation and clinical deployment pose additional challenge.

Yet another severe problem has been lack of explanation and interpretation that still prevents clinical use and physician reliance of deep learning frameworks. Moreover, very few papers have investigated multimodal learning approaches utilizing imaging, genomic, clinical, and demographic data and integrated them to support comprehensive diagnostic decision making. Taken together, the current state of research clearly suggests that hybrid deep learning architectures, Transformer-based ones, and optimization-assisted intelligent systems are the most promising avenues for the future development of bone cancer diagnosis systems. Models with the best performance are usually those that integrate transfer learning, multimodal feature fusion, ensemble learning, and optimization algorithms.

The research must focus on modeling large-scale multicenter datasets, improving explainable artificial intelligence techniques, and lowering computational complexities and designing clinically interpretable computer-aided diagnosis systems that are deployed reliably in real-world healthcare domains.

5.2 Research Gaps and Future Directions

Even with the progress of machine learning, deep learning and hybrid intelligent systems in detecting bone cancer, some major research gaps remain unresolved. Most of the literature works on small and imbalanced datasets produced by a single institution that may not be easily applicable and robust in real clinical environments. Moreover, some of the proposed schemes don't have external validation and do not consider multimodal integration between radiological, histopathological, clinical and genomic data. Additionally, the limited interpretability of deep learning models prevents their adoption in clinical practice due to the reduced trust and transparency of physicians. Moreover, the high computational complexity associated with advanced deep learning and Transformer-based architectures creates a challenge for actual clinical use. To enhance the reliability and practicality of hybrid intelligent systems trained on large-scale multicenter datasets, future research is necessary to provide explainable, lightweight, and clinically interpretable hybrid intelligent systems within the context of bone cancer.

6 Conclusion

Currently, Metaheuristic algorithm-enhanced DL frameworks can potentially become one of the most effective approaches for accurate and stable bone cancer detection in the future. CNNs are widely used in DL models , but GA, PSO and other metaheuristics have shown to be effective techniques for optimizing network architecture and parameters. Open source databases developed by the TCIA Osteosarcoma, BTXRD, SEER, Histopathology Osteosarcoma and other organizations have driven the progress of this field ,This survey found that the BTXRD dataset is one of the most suitable datasets for bone cancer detection research due to variation of cancer types also the number of images in data set more than 3740 image .MHA combined with DL enhances the classification accuracy and sensitivity as well as specificity when compared with standalone models Therefore, hybrid DL–MHA frameworks can significantly enhance computer-aided diagnosis and prognosis in bone oncology, supporting early detection, treatment planning, and precision oncology. Future research should focus on diversifying and benchmarking across multimodal datasets and developing models that are more interpretable to facilitate their integration into clinical practice .

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