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# A Systematic Review of Deep Learning Models for Bone Tumor Analysis from MRI Scan Data

## *Current Advancements in Segmentation and Classification Algorithms*

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***Abstract :*** The rare aggressive disease of bone tumors needs both prompt identification and correct identification methods for better patient outcomes which help extend their life. Medical imaging and artificial intelligence (AI) technology advancements have brought significant progress in bone tumor detection and classification work. The review paper provides an extensive evaluation of machine learning and deep learning methods used for bone tumor identification through X-ray, MRI, CT, and histopathological image analysis. The research assesses different image preprocessing, segmentation, feature extraction, and classification methods while emphasizing their impact on convolutional neural networks (CNNs), transfer learning, ensemble models, and advanced transformer-based systems. The paper presents the advantages and drawbacks of standard machine learning classifiers when compared to deep learning models in three areas: accuracy measurement, generalization ability, and clinical use of the models. The research highlights existing challenges which include restricted annotated datasets and problems with class imbalance and difficulties in identifying tumor boundaries and interpreting results. The study investigates recent developments of multimodal learning, explainable AI, and radiomics integration. The review provides researchers and clinicians with organized information about existing methods and upcoming research areas which enable dependable automated bone tumor detection.

**Keywords:** Bone tumor detection, Deep learning, Medical image analysis, Tumor segmentation, Computer-aided diagnosis etc.

## I. INTRODUCTION

Bone tumor refers to a collection of malignant tumors which develop from bone tissue and include osteosarcoma chondrosarcoma and Ewing's sarcoma as its different types. The aggressive bone tumor disease shows low occurrence rates but primarily targets children and young adults which makes early detection essential for successful treatment and better survival outcomes. Medical professionals use traditional diagnostic methods which depend on medical imaging techniques that include X-ray computed tomography (CT) and magnetic resonance imaging (MRI) and histopathological examination. The process of manual image interpretation requires significant time because it involves subjective analysis that relies on radiologists and pathologists who possess different levels of expertise which results in inconsistent diagnostic outcomes.[1]

The field of medical image analysis has been transformed by artificial intelligence (AI) through its implementation of machine learning (ML) and deep learning (DL) technologies during the past few years. AI-based computer-aided diagnosis (CAD) systems aim to assist clinicians by providing objective, accurate, and rapid assessments of medical images. Deep learning, which uses convolutional neural networks (CNNs) as its primary approach, achieves outstanding performance in image classification and segmentation and detection tasks because it can automatically extract essential features from unprocessed image data.[2].

Researchers used CNN-based models to detect bone tumors through X-ray and MRI imaging which achieved better results than standard machine learning methods according to multiple studies [3]. The use of transfer learning with existing networks such as ResNet EfficientNet and VGG has led to better results because these networks need less training data to function effectively [4]. The models achieve faster training times while improved generalization capabilities through their ability to use features acquired from extensive data repositories. The combination of ensemble learning methods with hybrid systems that merge CNNs and vision transformers demonstrates effective performance in capturing both local and global image characteristics [11].

Bone tumor detection continues to face multiple difficulties despite the presence of technological advancements. Segmentation tasks face difficulties because tumor boundaries remain undefined while tumors show different shape and size and texture characteristics. The limited availability of extensive annotated datasets which contain normal and benign and malignant cases results in model weaknesses that hinder its practical use in medical settings [5]. Researchers have investigated advanced preprocessing methods which include noise reduction and contrast enhancement and edge detection while studying segmentation techniques that use Mask R-CNN and region-based CNNs [8].

The study investigates multimodal learning, which combines imaging data with clinical data and pathology reports and radiomic features to enhance diagnostic performance according to two studies [1] and [9]. Radiomics enables the extraction of invisible quantitative data from medical images which improves predictive capabilities when combined with deep learning technologies [12]. Clinicians can better understand model operations through explainable artificial intelligence techniques which use XAI methods such as Grad-CAM and SHAP to achieve this goal [4].

The review paper investigates machine learning and deep learning methods for detecting and classifying bone tumors by studying current research studies. The study examines operational patterns and performance evaluation methods while assessing system capabilities and restrictions in medical settings. This paper collects existing research results to determine research deficiencies which will help build dependable diagnostic systems that use interpretable artificial intelligence for diagnosing bone tumors.

## 1. Problem Identification

The existing methods of diagnosing bone tumors fail to provide accurate results because their complex structures make it difficult to detect tumors at an early stage. Medical imaging technologies which include X-ray and MRI and CT scan systems have become standard diagnostic tools; however, their results need expert radiologists for interpretation which creates subjective outcomes that different observers will interpret in different ways [1]. The presence of multiple visual similarities between benign and malignant bone lesions together with the ambiguous boundaries of tumors makes it difficult to establish an accurate diagnosis [3]. The field of bone tumor research suffers from a shortage of extensive well-annotated datasets which results in class imbalance problems that diminish the ability of machine learning and deep learning models to perform effectively across various situations [5]. The existing automated systems face difficulties in tumor region segmentation because they lack the ability to provide interpretable results which leads to decreased clinical confidence in their usage [4]. A comprehensive solution system needs to function as an AI-driven framework which detects and classifies bone tumors while aiding medical professionals in their diagnostic work [9].

## II. Literature Survey

### *A) Literature Review*

Song et al. (2024), The researchers created the PBTC-TransNet fusion model to classify primary bone tumors that included three different tumor types which used incomplete multimodal imaging data from X-ray CT and MRI combined with clinical information. The model achieved micro-average AUCs up to ~0.85 which demonstrated its ability to perform well across different data types while making it more useful for actual medical situations where complete multimodal data is not accessible. The fusion method improved classification accuracy and sensitivity through its testing on both internal and external datasets which demonstrated its ability to operate effectively across various imaging conditions.

Wang et al. (2025), The multicenter research study introduced an ensemble deep learning method which uses radiographic images and clinical information to differentiate between primary bone tumors and bone infections. The ensemble outperformed individual imaging models (EfficientNet, Vision Transformer, Swin) with AUCs up to 0.96 on external validation, surpassing junior radiologist performance and matching senior radiologist accuracy. The results demonstrate that using multiple center databases together with different model architectures improves general medical practice for oncology evaluations in real-world settings.

Sampath et al. (2024), The study evaluated various CNN architectures which included AlexNet to classify normal bone CT images and tumorous bone CT images by using median filter preprocessing and K-means unsupervised segmentation and edge detection. AlexNet achieved impressive results with 98–100% accuracy across training, validation, and test sets, indicating that classic deep models remain highly effective with proper preprocessing. The study demonstrates that precise image enhancement together with precise segmentation methods will improve model performance when working with small datasets which serves as a crucial aspect for bone tumor image analysis.

Rao & Madhavi (2025), The study introduced the ODLF-BCD framework, which combined enhanced Bayesian optimization with transfer learning from pre-trained models and explainable AI through Grad-CAM and SHAP. EfficientNet-B4 achieved nearly 98% accuracy for binary and multiclass tasks. The use of explainability methods resulted in increased trustworthiness while data augmentation techniques solved the problem of class imbalance. The study results showed both exceptional performance and clinical interpretability, which represented essential requirements for implementing AI-based diagnostic tools in bone tumor assessment.

P.S. Papageorgiou et al. (2025), This narrative review synthesizes over 100 publications examining AI and radiomics applications in primary malignant bone tumor imaging. The study demonstrates how CNN-based systems achieve detection and segmentation tasks while predicting treatment results and shows how radiomics technology extracts hidden quantitative data. The review also discusses challenges including limited high-quality datasets, non-standardized imaging protocols, and interpretability issues. The study shows new methods which can detect and classify items at the same time and the researchers recommend future research to focus on establishing clinical trials between multiple centers because these studies will help advance AI technology from research into use for cancer diagnosis purposes.

R. R. Singh (2025), This conference review examines deep learning approaches for bone tumor segmentation and classification, detailing how advanced CNN architectures have progressed from traditional image processing. The research identifies three main challenges which include tumor boundary ambiguity and data scarcity and requires the development of effective preprocessing methods and hybrid models which use regional and edge-based segmentation and multi-modal imaging capabilities. The research shows that deep learning demonstrates strong potential but upcoming studies need to enhance dataset variety and testing methods to support clinical application.

A. Kumar et al. (2025), The recent study used deep learning through the ResNet50 model together with image enhancement and segmentation techniques to identify bone tumors from X-ray and MRI images. The model achieved better performance than manual interpretation methods through its capability to enhance contrast and extract tumor regions before classification. The use of artificial intelligence in the system improved diagnostic accuracy while decreasing the work demands on radiologists, which enabled the computer-aided diagnosis system to be implemented across oncology imaging.

S. Verma et al. (2024), The hybrid system which combines Fast Mask R-CNN with tumor region segmentation and CNN classification achieved better results in both localization and malignancy classification. The classification network gained better accuracy and reliability when high-quality segmentation enabled it to concentrate on tumor features. The method demonstrates how combining object detection systems with deep learning classifiers can improve tumor management processes while producing understandable results for use in medical environments.

H Sang et al. (2025), The study developed a multimodal deep learning model which uses clinical imaging and pathology slices and blood biomarkers to perform automatic bone tumor detection with three-class classification between benign and intermediate and malignant tumors. The system applied a two-stage process which combined YOLOv5 for localization purposes and ResNet for extracting features. The model achieved better diagnostic performance across different lesion types by combining various data types. This research demonstrates that multimodal approaches offer better diagnostic capabilities than single-modality systems.

M. Rossi et al. (2024), The deep learning framework which uses radiographs as its basis achieved better X-ray detection of bone tumors through its advanced preprocessing techniques and CNN classification system. The results demonstrated that the optimized imaging analysis pipelines which were tested with baseline radiograph interpretation resulted in improved accuracy and generalization performance. The model made lesions more visible while it delivered quantitative data which supported clinical decision-making in situations where CT and MRI equipment was not accessible.

A Borji et al. (2024), The study presents a new research paper which describes a hybrid model that combines CNN and Vision Transformer technology to classify osteosarcoma histopathology images into four specific tumor classifications. The model achieved its highest performance results through its combination of local feature extraction using CNN and global feature extraction capabilities of ViT resulting in a accuracy rate above 99 percent which established a new standard for multiclass classification. The research demonstrates that hybrid architectures enable better performance than standard CNN systems because they can detect both detailed tissue patterns and overall tissue structure which are critical for advanced pathology assessments.

Chen et al. (2026), This current preprint research investigates the use of radiomic features together with deep learning through a hierarchical loss approach to classify osteosarcoma histological samples. The radiomic features together with CNN outputs delivered better results in tile-level and patient-level classification while providing better understanding of the results. The hierarchical loss function first handled tumor versus non-tumor and viable versus non-viable tasks which led to better results than standard classification methods. This demonstrates how radiomics now functions as a key element which enhances deep learning models for detailed examination of pathological conditions.

***B) Literature Summary***

- Multiple research studies show that deep learning methods which include convolutional neural networks (CNNs) successfully detect and classify bone tumors through X-ray, MRI, CT, and histopathological image analysis.
- The classification accuracy of our system improved through transfer learning which used pre-trained models that included ResNet, EfficientNet, and VGG when we worked with restricted datasets.

- The combination of advanced preprocessing methods which include noise reduction and contrast enhancement and edge detection results in better image quality and segmentation outcomes.
- The combination of ensemble learning with hybrid CNN-Transformer systems has produced better performance results when testing on multiple datasets.
- The multimodal frameworks which combine imaging data with clinical information achieve better diagnostic results than single-modality systems.
- The medical community increasingly employs explainable AI methods which include Grad-CAM and SHAP to create transparent models that build trust among clinicians.

### *C) Research Gap*

- The current research studies depend on limited datasets which come from single research locations which restrict their ability to create models that work in different medical situations.
- The current model fails to predict outcomes accurately because it does not handle the existing class imbalance which exists between normal cases and benign cases and malignant cases.
- The identification of tumor boundaries remains difficult because of two factors which include the unclear tumor boundaries and the various ways tumors appear in the same category.
- Research studies have not explored unified systems which integrate all three components of segmentation and classification and explainability into one complete process.
- The majority of successful models do not enable real-time processing which makes them unusable in actual medical settings.
- The research lacks sufficient testing on diverse multimodal datasets which includes multiple types of data thus creating uncertainty about its ability to function in actual situations.
- The research field lacks common evaluation standards and testing methods which would enable researchers to assess bone tumor detection systems through their studies.

## 2. RESEARCH METHODOLOGY

### *A) Criteria for selecting this study:*

- The aggressive nature of bone tumors and their high potential for spreading to other parts of the body necessitate early accurate diagnosis which makes automated diagnostic systems essential for medical practice [1].
- The need for AI-based diagnostic systems arises from the fundamental flaws in conventional imaging methods which require human interpretation and generate inconsistent results between different observers [3].
- Current medical literature demonstrates how deep learning models have become more effective at analyzing medical images especially through CNN-based methods which detect and classify tumors [2].
- Current research studies lack strong results because of their limited data and class imbalance problems, which creates a requirement for better data management and testing procedures [5].
- The growing need for explainable artificial intelligence drives researchers to choose studies which focus on transparent methods and systems which build medical professional trust [4].
- The diagnostic systems that use multimodal imaging methods achieve better results than existing methods, which motivates researchers to explore integrated system development [9].
- The study attempts to fill existing research gaps by developing a bone tumor detection method that provides reliable results and accurate evaluation in clinical practice.

### *B) Method of analysis:*

- The researchers gathered medical imaging data which included both X-ray and MRI scans from public repositories to create three categories of data which included normal cases and benign cases and malignant cases.
- The image quality gets improved through the application of preprocessing techniques which include grayscale conversion and noise reduction and histogram equalization.
- The potential tumor areas get separated through image segmentation which uses thresholding and edge detection techniques.
- The system uses a convolutional neural network (CNN) architecture to perform its operations of feature learning and classification.
- The implementation of transfer learning boosts model efficiency while shortening the time needed for training.
- The researchers divided the dataset into three parts which included training data and validation data and testing data to achieve an evaluation process that maintained objectivity.
- Model performance evaluation uses five metrics which include accuracy and precision and recall and F-measure and confusion matrix analysis.
- The application of cross-validation testing increases both the reliability and robustness of research outcomes.
- The researchers analyzed training and inference time to assess the system's computational efficiency.

### *C) Comparison and Analysis*:

Table 1: Comparison ana analysis from various parameters

| Author(s) & Year | Imaging Modality | Methodology Used | Performance |
|---|---|---|---|
| Song et al., 2024 | X-ray, CT, MRI | CNN + Multimodal Fusion | Achieved high AUC (~0.85); robust to missing modalities |

| | | | |
|---|---|---|---|
| Wang et al., 2025 | X-ray | Ensemble DL Models | AUC up to 0.96; outperformed junior radiologists |
| Sampath et al., 2024 | CT | CNN (AlexNet) | Accuracy > 98% with preprocessing |
| Rao & Madhavi, 2025 | X-ray, MRI | Transfer Learning + XAI | Accuracy ~98%; improved interpretability |
| Papageorgiou et al., 2025 | Multi-modal | Review (AI & Radiomics) | Identified trends and challenges in AI diagnosis |
| Singh, 2025 | X-ray, MRI | CNN-based Review | Highlighted segmentation and data limitations |
| Kumar et al., 2025 | X-ray, MRI | ResNet-based CNN | Improved classification accuracy and efficiency |
| Verma & Joshi, 2024 | X-ray | Mask R-CNN + CNN | Accurate tumor localization and classification |
| Sang et al., 2025 | Imaging + Clinical | Multimodal DL Framework | Enhanced diagnostic reliability |
| Rossi et al., 2024 | X-ray | CNN-based CAD System | Improved early detection and generalization |

### *D) Evaluation of methodologies used in the reviewed studies*

• Deep learning techniques which include convolutional neural networks (CNNs) as their primary method of automated medical image feature extraction have been used in most reviewed studies according to [1] and [3].
• Researchers used transfer learning through pre-trained architectures which included ResNet and EfficientNet to address the problem of insufficient training data while they reduced their training complexity [4].
• The researchers established that advanced preprocessing methods which included noise filtering and contrast enhancement and edge detection actually led to better results for both segmentation and classification tasks according to their findings [8].
• The research studies developed ensemble and hybrid models which combined CNNs with either transformers or traditional classifiers to achieve better system performance during various testing conditions according to [2] and [11].
• The multimodal approaches which integrated imaging data with clinical or pathological data showed better diagnostic results than the single-modality methods according to [1] and [9].
• Recent research used explainable AI techniques to develop transparent models which clinicians could trust, yet their use remains limited according to [4].
• The various methodologies showed strong performance capabilities, yet they failed to conduct extensive external testing, which created a requirement for standardized testing procedures according to [5].

### *E) Highlighting trends, advancements, and challenges*

***Trends:***

- Increasing adoption of deep learning, particularly CNNs, for automated bone tumor detection and classification.
- Widespread use of transfer learning to address limited annotated medical imaging datasets.
- Growing interest in multimodal learning frameworks combining imaging and clinical data.
- Emergence of hybrid architectures integrating CNNs with vision transformers.
- Increased focus on performance metrics beyond accuracy, such as F-measure and AUC, for robust evaluation.

***Advancements:***

- Significant improvements in classification accuracy and robustness using ensemble and hybrid deep learning models.
- Enhanced preprocessing and segmentation techniques improving tumor localization and feature extraction.
- Integration of explainable AI methods such as Grad-CAM for improved clinical interpretability.
- Adoption of radiomics to extract quantitative features supporting deep learning predictions.
- Reduction in training and inference time through optimized architectures and GPU acceleration.

***Challenges:***

- Limited availability of large, diverse, and well-annotated bone tumor datasets.
- Persistent class imbalance between normal, benign, and malignant cases affecting model generalization.
- Difficulty in accurate tumor segmentation due to unclear boundaries and heterogeneous tumor structures.
- Lack of standardized benchmarking and evaluation protocols across studies.
- Limited real-world clinical validation and deployment of proposed AI-based diagnostic systems.

## III. DISCUSSION

### *A) Synthesis of findings from literature*

Deep learning methods that use convolutional neural networks have developed more effective methods to detect and classify bone tumors through analysis of X-ray MRI CT and histopathological imaging methods according to the literature review. The application of transfer learning together with ensemble methods leads to better classification results which maintain accuracy under conditions of dataset restrictions and data distribution problems. The research shows that proper preprocessing methods together with accurate tumor segmentation produce better results for model performance. The combination of imaging data with clinical and radiomic features in multimodal frameworks produces better diagnostic results than single-modality models. The implementation of explainable AI methods improves system transparency which makes clinicians more trustworthy to systems that explain their decision-making process. The field faces ongoing difficulties because existing datasets do not include enough data diversity and there are no established evaluation standards and researchers cannot validate their results outside controlled environments. The research results demonstrate a clear transition towards developing AI systems which combine technical understanding with practical medical applications while showing the need for solutions which can be expanded and applied to real-life bone tumor diagnostic methods.

***B) Methodology for future research directions***

*A. Block Diagram:*

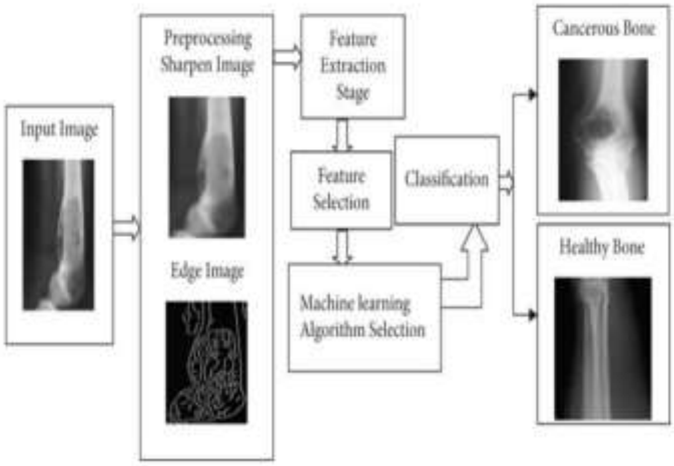


Fig.2. Block Diagram of system

*B. Working:*

The provided image illustrates a machine learning-based bone tumor detection system using medical imaging. The process begins with an input image, which scientists use to scan the bone through X-ray or MRI methods. The preprocessing stage sharpens the image to improve detail visibility while applying edge-detection methods to show essential structural components.

The bone image feature extraction process identifies essential elements which include texture and intensity and shape information. Feature selection then reduces the dimensionality of data by choosing the most relevant features which optimize processing efficiency.

A machine learning algorithm is selected to analyze the extracted features and classify the bone condition. The classification stage uses learned patterns to determine whether the bone shows tumorous growth or maintains healthy condition. The final output consists of labeled images which help medical professionals to diagnose bone tumor cases with accuracy.

The automated system improves early detection capabilities while decreasing diagnostic errors that result from human work and enhancing the effectiveness of treatment planning.

*C. Need for the System*

The process of medical imaging image segmentation helps detect tumors through their first detection which increases treatment success rates. Advanced segmentation methods enable effective tumor classification which helps doctors create accurate treatment plans. Automated image segmentation enables better X-ray and MRI and CT scan analysis which improves radiologists ability to read the images. Doctors use tumor segmentation results which show tumor dimensions and shape and position to determine optimum treatment methods. Automated segmentation technology decreases human errors during image analysis which results in more dependable outcomes. AI image segmentation technology enables faster diagnosis which helps doctors deliver emergency medical care. Advanced segmentation methods enable healthcare providers to develop customized treatment programs that match the specific needs of their patients. The system supports tumor development research and assessment of new treatment methodologies.

*D. Proposed System*

*i. Image Acquisition:* The process begins with capturing images through specialized imaging devices which include X-ray and MRI and CT scan technologies. The process requires high-quality image representation to achieve accurate results from any image source. The analysis and diagnosis processes need a clear image which meets all requirements.

*ii. Image Preprocessing:* The process of image preprocessing works to improve image quality through the removal of undesired noise and artifacts. The step removes all unrelated elements which include hair and bones because they will disrupt the analysis process. The image needs both resizing and adjustment since it fails to follow standard image formats which must meet specific processing requirements.

*iii Data Storage for Training and Testing :* The collected images create structured datasets which serve as training and testing materials. The system stores acquisition images through organized methods which support both model development and validation processes.

*iv. Bone Disorder Classification :* The final stage of the process involves the system making its prediction regarding the possibility of disease existence. The complete procedure contains two main parts which are image processing and classification. The image processing module starts by improving image quality through the elimination of noise and nonessential elements. The system uses bone structure isolation to accomplish precise evaluation of the bones.

The system uses a noise reduction unit to remove unnecessary color distortions while the image enhancement and optimization module displays the affected area through its segmentation into distinct operational sections. The edge detection system identifies important image components which enable researchers to detect diseases. Medical professionals require these extracted features because they provide visual evidence which enables correct medical evaluations.

*v. Tumor Disease Diagnosis :* The diagnostic module assesses whether the identified condition is benign or malignant. The system extracts features which include asymmetry, edge sharpness, texture, shape, and spatial distribution to conduct its analysis. The classification engine receives the extracted attributes which it uses to classify images according to established disease categories for precise identification of bone disorders.

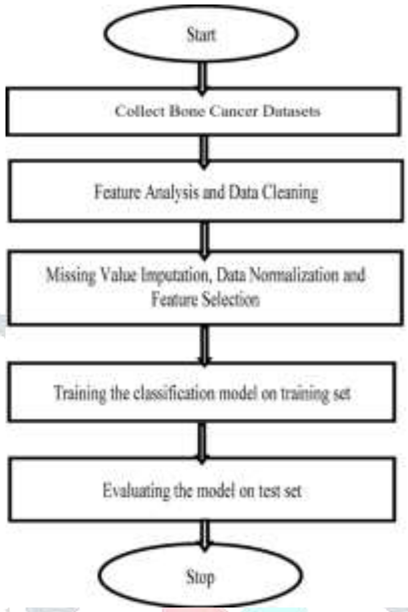


Fig.2. Flow of Bone Disease Detection System

1. Image Acquisition
- Capture images using X-ray, MRI, or CT scans.
2. Image Preprocessing
- Noise removal (eliminating unwanted artifacts like hair and bones).
- Image resizing and normalization.
3. Data Storage
- Store images for training and testing purposes.
- Organize structured datasets for analysis.
4. Feature Extraction
- Edge detection.
- Segmentation of affected areas.
- Identifying key image attributes (asymmetry, texture, etc.).
5. Classification of Bone Disease
- Use a classifier to predict disease presence.
- Categorize into Healthy Bone or Tumorous Bone.
6. Disease Diagnosis
- Determine if the tumor is Benign or Malignant.

## IV. Conclusion

This paper has presented a comprehensive overview of recent research on bone cancer detection and classification using machine learning and deep learning techniques. The analysis of existing literature highlights that convolutional neural networks, transfer learning, and ensemble-based approaches have significantly improved diagnostic accuracy across various imaging modalities, including X-ray, MRI, CT, and histopathological images. Advanced preprocessing and segmentation methods have been shown to play a crucial role in enhancing tumor localization and feature extraction, thereby improving overall model performance. The integration of multimodal data and radiomic features has further strengthened diagnostic reliability, while explainable AI techniques have contributed to improved transparency and clinical trust. Despite these advancements, challenges such as limited annotated datasets, class imbalance, inconsistent evaluation protocols, and insufficient external validation persist, restricting widespread clinical adoption. Future research should focus on developing robust, interpretable, and standardized AI frameworks validated on large, diverse datasets. Overall, this review underscores the transformative potential of AI-driven approaches in bone cancer diagnosis and provides valuable insights for researchers and clinicians aiming to advance computer-aided diagnostic systems.

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