

A Comprehensive Review of Transfer Learning Models for Automated Detection of Soft Tissue Sarcoma and Osteosarcoma

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Abstract:

This is a review of a wide range of research papers that are dedicated to the use of machine learning (ML) in cancer detection. The review summarizes the techniques used in different studies and demonstrates that the significance of ML plays a crucial role in properly identifying tumors in different medical imaging techniques including MRI, CT scans, and histopathological images. The observations by the paper utilising convolutional neural networks (CNNs), deep learning frameworks and ensemble algorithms all demonstrate the importance of these approaches in accurate image analysis, segmentation and classification of tumours. In addition, this review engages in the compilation of multimodal data and the application of radiomic features to multifactorial characterization of a tumor. It also puts an emphasis on the ML-driven clinical decision support systems, explaining how they can help healthcare professionals make accurate diagnostic tests, individualized treatment plans, and forecast treatment results. The discussion also illuminates the existing constraints, ethical issues, and future outlooks of cancer detection using AI/ML. Identifying weaknesses in the interpretability of ideas and the necessity of strong regulatory measures, the review highlights how the ML will transform the diagnostics of cancer and preconditions further innovation in the sphere of this important area of medical practice.

Keywords: Sarcoma Detection, Osteosarcoma Classification, Machine Learning in Medical Imaging, Transfer Learning, Deep Learning for Cancer Diagnosis, Medical Image Analysis.

1. Introduction

One of the major bone cancers is the osteosarcoma that is very aggressive and is exhibited predominantly among the adolescents and the young adults. The diagnosis of sarcoma and osteosarcoma is a clinical issue that needs to be solved at an early and accurate diagnosis because of the complicated histological appearance, a variation of the presentation of such tumors, and the relative rarity compared to other forms of cancers. The conventional form of diagnostic methodologies involve application of imaging tests as a diagnostic technique mode like magnetic resonance imaging (MRI), computed tomography (CT) and the X-ray imaging, coupled with histopathological examination. The techniques are however highly demanding with regards to the professional interpretation and are prone to inter-observer and delayed diagnosis. The latest developments in artificial intelligence (AI) and machine learning (ML) have also presented further prospects in terms of optimization of the medical image analysis, and computer-aided diagnosis of cancer. Specifically, the deep learning algorithms, in particular, convolutional neural networks (CNNs) and the transfer learning algorithms have proven to be extremely successful concerning the feature extraction, tumor segmentation, and tumor classification in the majority of medical imaging tasks. These methods allow studying the complex pattern of imaging mechanically and assist clinicians in identifying the less evident pathological manifestations which cannot be easily identified with the assistance of the traditional diagnostic procedures. This is why it has been proposed that the AI-based diagnostic systems may be the solution to the improvement of the specificity of diagnostics, its efficiency, and reproducibility in diagnosing sarcoma.

Application of machine learning algorithms in the detection and classification of sarcoma and osteosarcoma using a wide range of data modalities, including radiological imaging, histopathology slides, genomic data, and clinical records have been investigated in a range of papers over the past few years. The classical machine learning models, which are popular in predictive modelling and survival analysis, are Support Vector Machines (SVM), random forest, and logistic regression but more complex deep learning models, such as resnet, densenet and attention-based neural networks have shown to be more successful in automated tumour detection and grading. Even faster development in the field has also been made possible by transfer learning algorithms, which can scale models that have been trained on large data sets, including medical imaging ones, to smaller ones, which has been considered one of the biggest problems of medical AI applications. Despite these attainments, several problems are encountered during the application of AI-based sarcoma detection systems which include limited annotated data, variability of imaging protocols, model explainability, and robust clinical validation. Therefore, it is necessary to conduct a general literature review to understand the current level of development, gaps and new trends in machine learning-based sarcoma diagnosis.

The presented review article is a comparative and systematic review on machine learning solutions that have been applied in the detection and diagnosis of sarcoma and osteosarcoma. The literature review also examines the literature that employs alternative imaging modalities (including MRI, CT scan, X-rays and histopathological images) and also multimodal data integration techniques utilizing imaging data with genomic and clinical data. The main metrics of performance are accuracy, sensitivity, specificity, area under the receiver operating characteristic curve (AUC), and the impact of the computational efficiency and model interpretability and the potential impact of the model on the clinical practice.

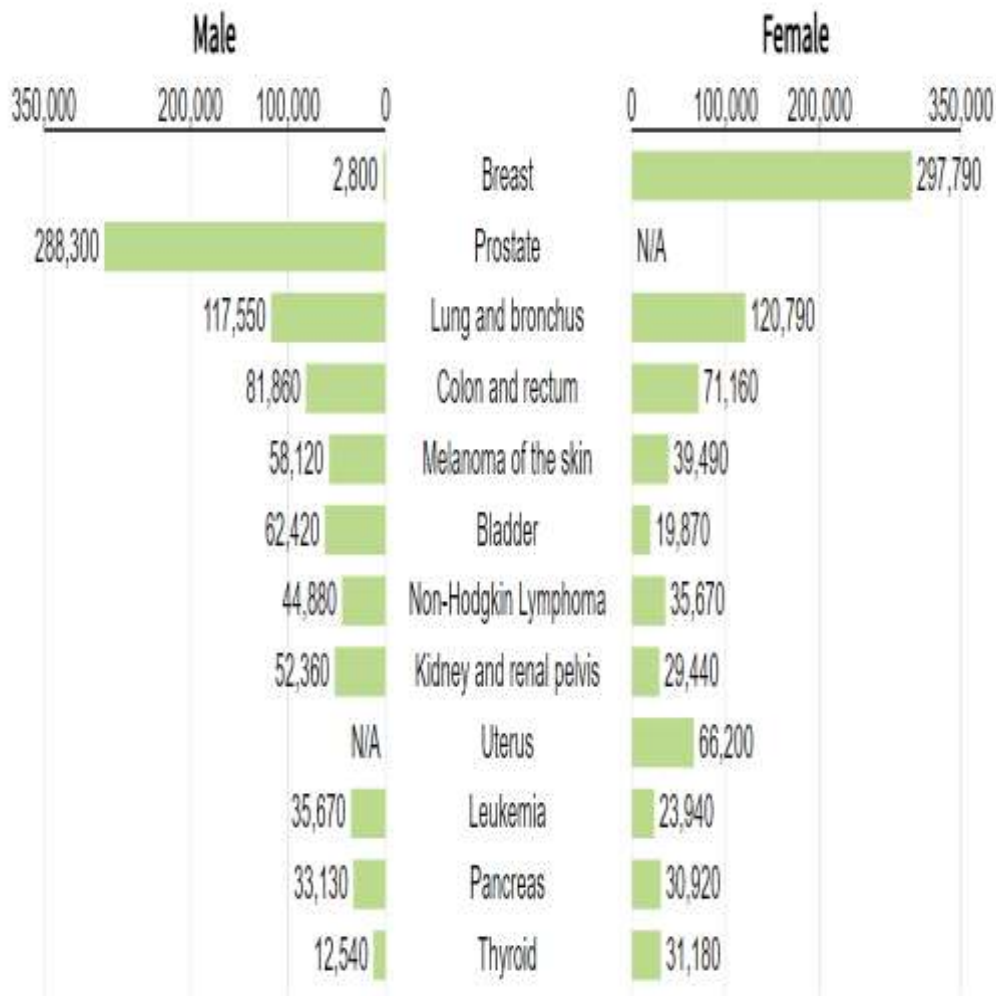
The significant objectives of this review are four-fold:

- Provide the general knowledge of sarcoma and osteosarcoma, their issues of diagnosis and clinical significance;
- Compare and contrast machine learning and deep learning methods to the diagnosis of sarcoma in different modalities in medical imaging;
- Determine the role transfer learning and multimodal combination of information in enhancing diagnostic accuracy and predictive performance; and
- Identify the gaps that are present in the studies, constraints, and the potential future paths of the development of the useful AI-based diagnostic tools to detect sarcoma.

1.1 MOTIVATION

The increasing cancer incidence and mortality across the world underscores the ever-increasing demand of superior diagnostic models capable of aiding the early diagnosis and enhancing the clinical outcome. Sarcoma and osteosarcoma are especially tricky malignancies since they are not very common, their tumor structures are heterogeneous, and they have varied anatomy, thus in most cases, early diagnosis is hard. The traditional methods of diagnosis are based on radiological visualization and histopathological analysis that involves a great amount of professional interpretation, and can be characterized by inconsistency in clinical evaluation. As Figure 1 shows, the dispensation of cancer diagnosis levels in men and women population evidences the pervasive nature of cancer, which proves the need to create more efficient diagnostic technologies that could aid the prompt and correct diagnosis of the cancer.

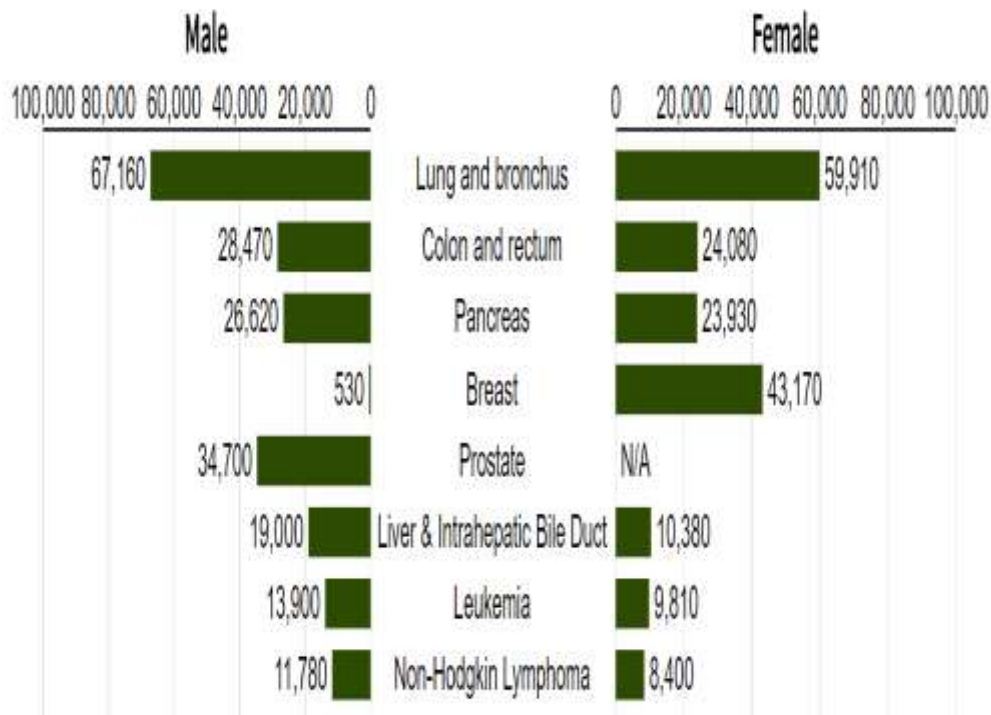
Figure 1. Distribution of cancer diagnoses among male and female patients across different cancer types



(Source: seer.cancer.gov, Cancer Facts & Figures 2023, American Cancer Society (ACS), Atlanta, Georgia, 2023)

This is because cancer related death is one of the most significant health challenges in the world despite the emergence of imaging and clinical diagnostic. The mortality curves of different forms of cancers raised in Figure 2 show that more should be done to come up with better detection and prognostic tools that can enable clinicians to track the occurrence of aggressive cancers at an earlier stage. The idea of AI and ML became one of the strongest acquisition methods to medical imaging and computational diagnostics in the previous few years. They can be used to extract features, tumor segregation and classification of complex medical data automatically, and develop diagnostic accuracy, reduce interpretation time and support clinical decision-making in challenging diseases such as sarcoma and osteosarcoma.

Figure 2. Deaths due to cancer among male and female patients with various cancer types.



(Source: seer.cancer.gov, *Cancer Facts & Figures 2023*, American Cancer Society (ACS), Atlanta, Georgia, 2023)

Based on such developments, this review aims to review and synthesize the literature on machine learning-based sarcoma and osteosarcoma detection methods that have been published. The review will be focused on the disclosure of the methodological trends, the evaluation of the presented performance outcomes and identification of the research gaps through the lenses of the studies which apply various imaging modalities, ML algorithms, and deep learning architectures. Such analysis is necessary to understand the part that AI-based diagnostic systems play in helping to make more accurate, cost-effective, and scalable cancer detection models effective in clinical practice.

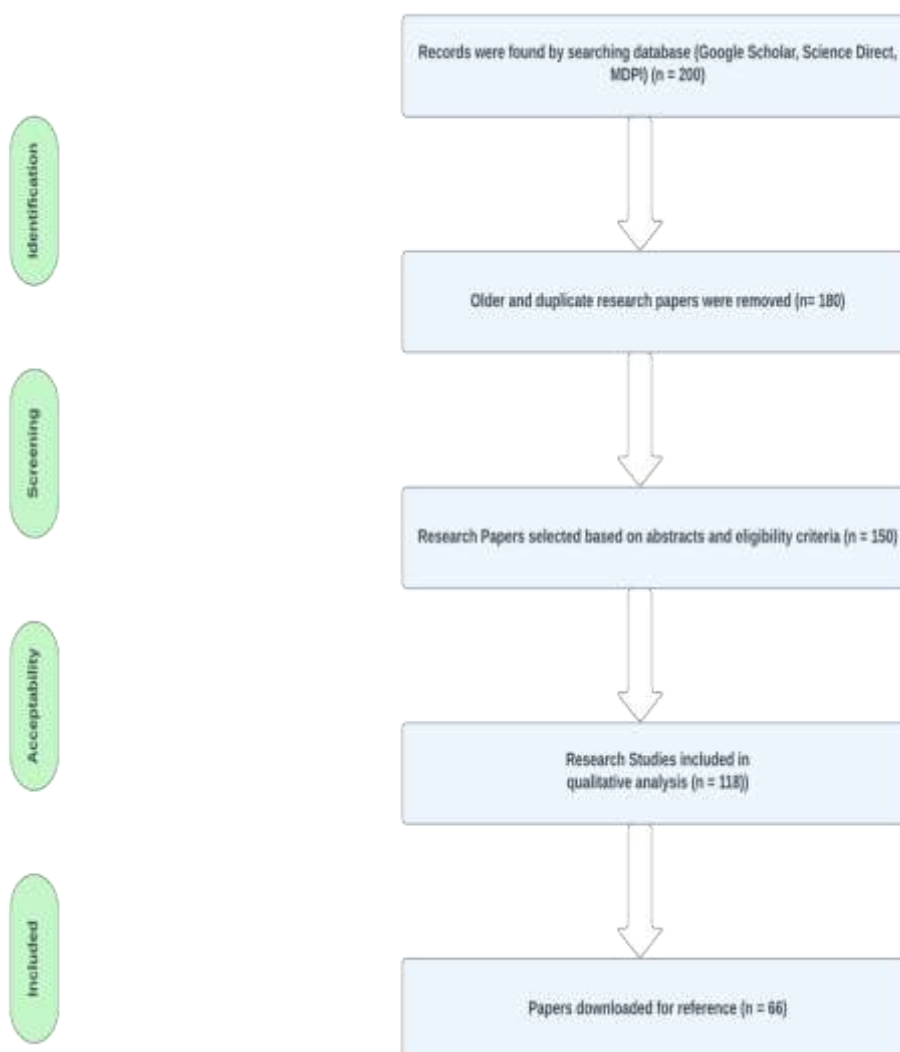
1.2 RESEARCH METHODOLOGY:

The proposed review will be performed in the framework of a systematic literature review study design to investigate the available literature sources devoted to the use of Artificial Intelligence (AI) and Machine Learning (ML) algorithms to detect and diagnose sarcoma and osteosarcoma. The approaches of the study adhere to the requirements of the Preferred Reporting Items of Systematic Reviews and Meta-Analyses (PRISMA) framework to render the process of identifying and selecting the required studies transparent, reproducible, and methodological.

A systematic search strategy was applied to locate literature in large academic databases in order to arrive at the relevant literature. The keywords to find Google Scholar, scienceDirect, and MDPI publications were Artificial Intelligence, Machine Learning, Deep

Learning, Sarcoma Detection, and Osteosarcoma Classification. The articles published in 2011 and above were considered only, as it is necessary to ensure that the review will be based on the up-to-date trends in AI-based medical imaging and cancer detection. The initial search gave 200 research articles which were subjected to a multi-stage search. Figure 3 shows that the screening and selection process relied on the PRISMA methodology. One hundred and eighty papers were then retained due to the filtering of old and repetitive records that had to undergo additional evaluation. Based on the titles and abstracts, 150 papers were filtered that had passed the initial eligibility criteria. Subsequently, full-text analysis has been conducted in detail to determine the applicability to AI-based sarcoma and osteosarcoma detection. After the inclusion and exclusion criteria, the qualitative analysis of the study sample comprised 118 studies. Among them, 66 articles were subsequently downloaded and examined in depth to help in the literature synthesis and comparative analysis as put in this review.

Figure 3. PRISMA-based literature selection process for the systematic review.



According to the chosen literature, the following research investigations are discussed in

terms of this review:

Investigation 1: To define the machine learning and deep learning techniques that have good performance to predict the presence or absence of sarcoma and osteosarcoma.

Investigation 2: To explore whether transfer learning methods enhance the stability and precision of AI-based systems to detect sarcoma.

Investigation 3: To establish the medical imaging modalities (MRI, CT scans, X-ray, or histopathological images) with the best prediction accuracy when it comes to diagnosing sarcoma and osteosarcoma.

Investigation 4: To examine the technical and practical issues that researchers encounter in the process of creating AI-based predictive models, which can be applied in detecting sarcoma.

2. MEDICAL SECTOR METHODOLOGIES FOR CANCER PREDICTION AND DETECTION

The recent advances in computational oncology have significantly improved the ability of the health systems to detect and analyse cancer according to information-driven methods. Particularly, the artificial intelligence (AI) and machine learning (ML)-based approach have made it possible to process medical images, molecular biomarkers and clinical data automatically to diagnose early cancer. The technologies are highly significant in the accuracy in diagnostics, tumor characterization, and in the clinical decision-making process. Relevant to the example of sarcoma and osteosarcoma diagnostics, current diagnostics pipelines utilize imaging, molecular profiling, histopathology, and machine learning models to discover useful patterns in the complex medical information. The tumor morphology can be imaged in detail using magnetic resonance imaging (MRI), computed tomography (CT) and ultrasound imaging but molecular and genetic assays can be used to identify biomarkers that associate with the development of tumours. Moreover, the deep learning algorithms can automatically find hierarchical information in the imaging and histopathological data and can be applied to the automatic classification and segmentation of tumors. This combination has led to the development of improved clinical decision support systems, which could improve their rate of detection and quality of diagnoses. In the medical industry, Table 1 underlines the main technological approaches, which are being implemented nowadays in the process of predicting and detecting cancer.

Table 1. Review of Medical Sector Methodologies for Cancer Prediction and Detection

Methodology Category	Techniques / Tools	Data Sources	Key Advantages	Limitations
Medical Imaging	MRI, CT Scan, Ultrasound, X-ray, PET scans	Radiological images	High spatial resolution for tumor localization	Expensive equipment, expert interpretation required
Radiomics	Texture analysis, GLCM features, shape	MRI, CT imaging datasets	Quantitative tumor characterization	Sensitive to imaging variations

	descriptors			
Molecular Profiling	Gene expression analysis, biomarker identification	Genomic and molecular datasets	Enables personalized medicine	Requires large genomic datasets
Histopathological Analysis	CNN-based classification, digital pathology	Tissue biopsy images	High diagnostic accuracy for tumor type	Requires annotated datasets
Machine Learning Models	SVM, Random Forest, Logistic Regression	Clinical + imaging datasets	Efficient predictive modeling	Feature engineering required
Deep Learning Models	CNN, ResNet, DenseNet, U-Net	Imaging datasets	Automatic feature extraction	Data-hungry models
Transfer Learning	Pre-trained CNN models	Small medical datasets	Improves performance with limited data	Domain adaptation challenges
Multimodal Data Fusion	Integration of imaging, clinical, and genetic data	Multi-source datasets	Improved diagnostic robustness	Complex system integration

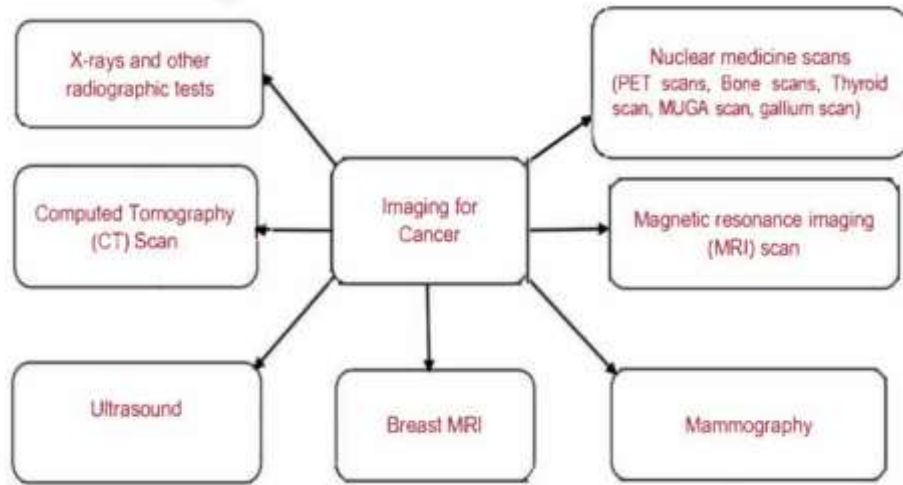
The techniques employed in the medical field to detect and predict cancer can be more or less classified into imaging-based diagnostic programs, molecular and genomic profiling techniques, histopathological studies, and predictive models systems driven by artificial intelligence.

2.1 Imaging-Based Cancer Detection Techniques

Medical imaging technologies are the leading diagnostic methods employed in the clinical practice in order to detect cancerous tumors. Such methods enable the doctors to see the internal organs and identify any unusual growth in tissues. Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Ultrasound and X-ray imaging are some of the imaging modalities usually used to determine tumor size, location, and structural features. Besides the conventional imaging technique, nuclear medicine techniques like PET scan, bone scan divulges metabolic detail concerning tumor activity. These technologies are the basis of the modern cancer diagnostics, and are commonly used with the computational analysis

techniques to enhance the detection of the tumor.

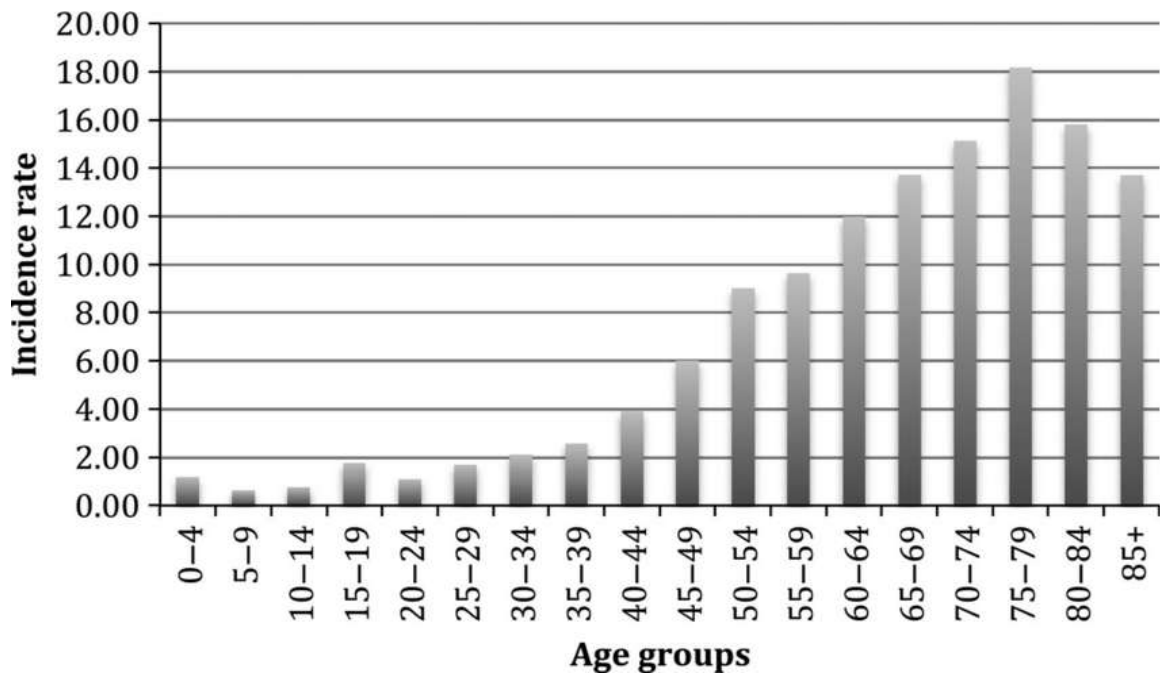
Figure 4. Imaging modalities used in cancer diagnosis



3.2 Age Distribution and Epidemiological Patterns of Sarcoma

The epidemiology of sarcoma gives valuable outcomes on the prevalence and the risk factors of the disease in the various age groups. Sarcomas of the soft tissue may develop at any age, but the rates of their occurrence are greatly different in relation to demographic factors and the type of tumor. The distribution of the cases of soft tissue sarcoma is shown to grow in the middle of adulthood as shown in Figure 7 with the majority of the cases being exhibited between the ages of 30 and 60. The awareness of such epidemiological patterns is necessary to categorize the high-risk groups and develop a specific screening strategy that could be relevant to enhance the rate of early detection.

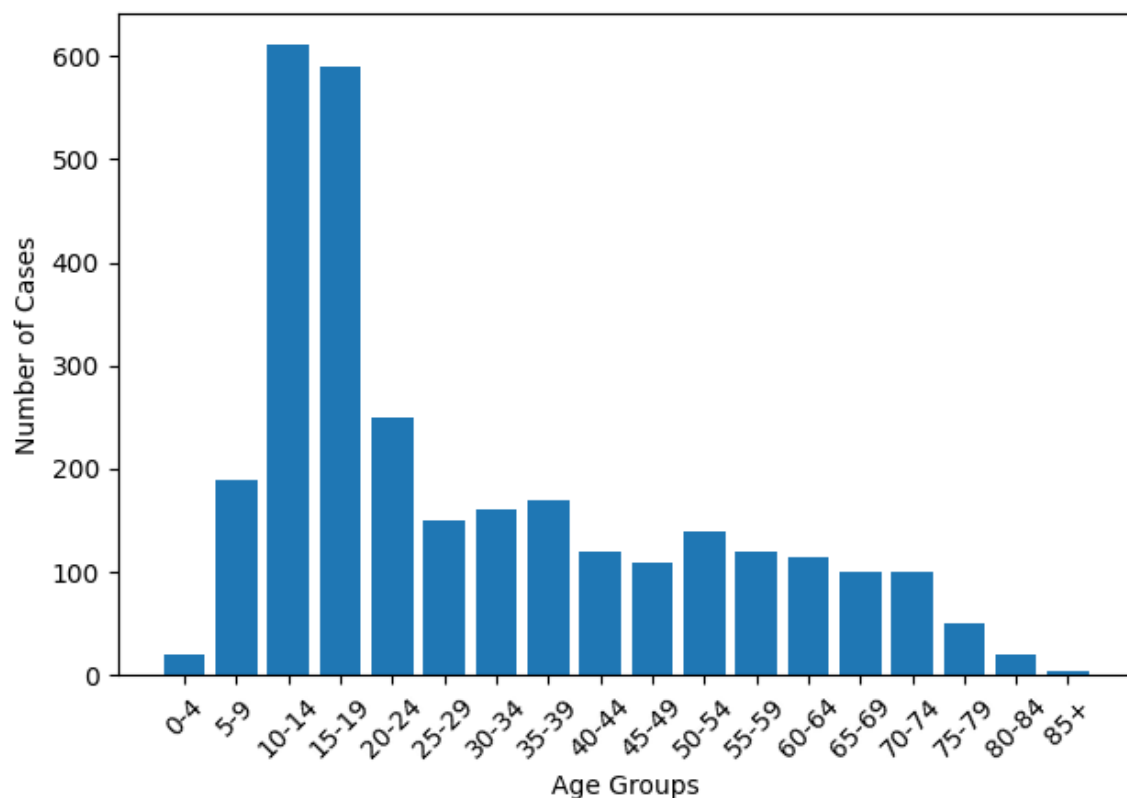
Figure 5. Age distribution of soft tissue sarcoma incidence across different age groups



2.3 Osteosarcoma Age Distribution and Risk Patterns

The epidemiologic trend of the occurrence of osteosarcoma is not similar to other forms of sarcomas. The disease affects the adolescents and young adults the most at that age where a high rate of growth of the skeletal structure is registered. However, there are also secondary incidence peaks that are observed among the elderly due to bone diseases or as a result of hereditary tendencies. Figure 8 illustrates the age distribution of the osteosarcoma cases with the highest levels of the diagnosis being made among the teenagers and young adults. These demographic patterns are applicable in order to inform the clinical surveillance strategy and understand biological mechanisms of osteosarcoma etiology.

Figure 6. Age distribution of osteosarcoma cases among different age groups.



(Source: Lee, Jun Ah, et al. "Osteosarcoma in Adolescents and Young Adults." *Cells*, vol. 10, no. 10, Oct. 2021, p. 2684. www.mdpi.com, <https://doi.org/10.3390/cells10102684>.)

2.4 AI and Machine Learning Techniques for Cancer Detection

One of the fields where artificial intelligence has proven to be a disruptive technology is in the medical field of diagnosis especially cancer diagnosis through images. Machine learning would then be capable of being used with large amounts of medical data and discover intricate patterns that might be difficult for human specialists to determine. CNNs are also commonly applied in the study of medical imagery as they can potentially learn feature representations of hierarchical features on medical imaging data. These models are capable of high accuracy in detecting, segmenting, classifying tumors, etc.

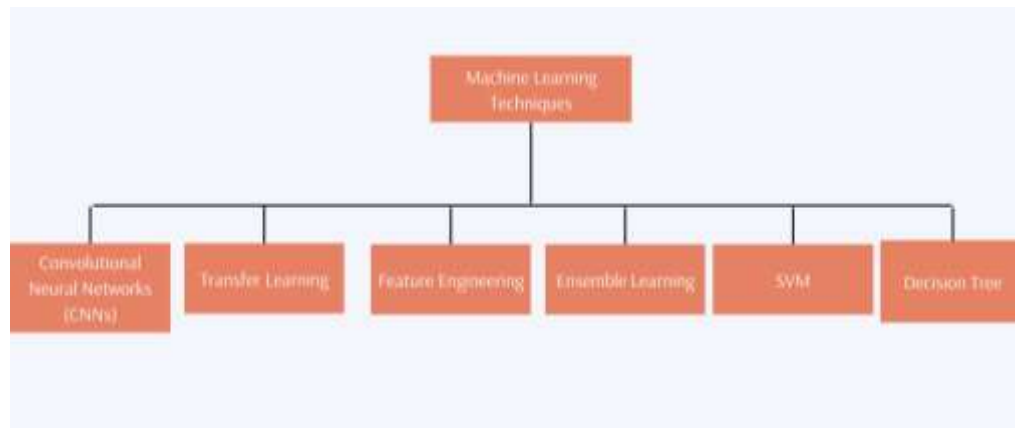
Transfer learning, as well as CNNs, is actively used by researchers in medical imaging who are willing to train pre-trained deep learning models, including ResNet, VGG, and Inception,

to learn how to differentiate sarcoma and osteosarcoma. The ensemble learning techniques that involve the combination of predictions of several machine learning models also increase the predictive performance and resilience. Moreover, the multimodal data fusion tools also combine the imaging data with the clinical or genomic data to come up with an integrated predictive systems that can be used in clinical decision making. In spite of these inventions, these issues combined with the labeled data as a constraint, model interpretability, and the cross-institutional generalization are dire threats to a widespread clinical adoption of AI cancer detection systems.

3. RELATED WORK

The medical imaging and cancer diagnostics have changed greatly with the usage of Artificial Intelligence (AI) which allows working with the complex biomedical data and enhances the correctness of determining the disease. The application of algorithmic machine learning (ML) and deep learning (DL) to the medical imaging processes has been employed in recent years, and it enabled researchers to create intelligent diagnostic models that were able to determine the presence of cancerous tumors in radiological and histopathological images. The conventional methods of diagnosis are based mainly on manual analysis of the imaging data provided by the clinical specialists and the process might be time-consuming and open to subjective judgments. Overcoming these disadvantages, AIs used to provide diagnostic models automatically recognize the important patterns of the medical images and can identify the characteristics of the tumor development. Specifically, neural networks (CNNs) deep learning architectures have fared well in tumor segmentation, classification and detection. These models may be applied to the learning of hierarchical representations with large datasets and in this case one can find and detect abnormal tissue structures with the required accuracy. Other literature has been conducted alongside CNN based designs to determine the value of transfer learning techniques in enhancing performance in medical image tasks. The training of ResNet, VGG and Inception in medical image classification is enabled by transfer learning and thus overcomes the shortage of annotated data. Moreover, radiomics has emerged as a significant research trend in cancer diagnosis. Radiomics is concentrated on derivation of quantitative image characteristics including texture, shape and intensity of medical images and may be applied to describe the heterogeneity of the tumor and forecast the prognosis of the treatment. The Support Vector Machines (SVM), the Random Forest and the Decision Trees are the common machine learning algorithms that have been applied to these radiomic features when it comes to classification and predictive modelling. Moreover, the ensemble learning methods apply projection of several models by taking the pool to enhance the precision of the diagnostics and to mitigate the bias of prediction. This kind of combination of such methods of computation has resulted in the creation of sophisticated clinical decision support systems that can be utilized by physicians to assist them with diagnosing and planning the therapy of cancer. Such AI-based diagnostic models have demonstrated a significant potential of raising their early-diagnosis of such forms of cancers as sarcoma and osteosarcoma that are heterogeneous in their tumor structure and relatively low in occurrence. Artificial intelligence in medical imaging is thus a significant field of study in computational oncology.

Figure 7. Machine learning techniques used for cancer detection



The machine learning algorithms provide a mechanical approach to the interpretation of medical data and identification of the trends to the tumor characteristics. One of such methods is the convolutional neural networks and it has found its application in the medical image analysis, due to its capability to learn the hierarchical feature representations of the imaging data in an automatic manner. U-Net and DenseNet CNN based structures have proved to be excellent in activities that involve tumor segmentation and have managed to localize the tumor boundaries on MRI and CT images intelligently. In addition, the transfer learning techniques provide the researcher to apply an already trained model of deep learning to medical images with significantly improved performance when the dataset is unlabeled.

Table 2. Summary of AI-Based Studies for Sarcoma and Osteosarcoma Detection

Study	Disease Focus	Data Source	Methodology	Key Contribution / Outcome
Nabid et al.	Osteosarcoma	Histological tumor images	Sequential Recurrent Convolutional Neural Network (RCNN)	Proposed a deep learning framework for automated classification of osteosarcoma tumors from histopathological images, demonstrating improved feature extraction and tumor pattern recognition.

Jiang et al.	Osteosarcoma	SEER database (2004–2017)	Extreme Gradient Boosting (XGBoost)	Developed a survival prediction model for osteosarcoma patients, achieving high predictive accuracy with AUC values of 0.977 (training) and 0.911 (validation).
Zhong et al.	Osteosarcoma	PET, MRI, and CT radiomics datasets	Radiomics feature extraction and statistical modeling	Evaluated radiomics-based predictive models for treatment response and prognosis in osteosarcoma, highlighting methodological limitations affecting clinical translation.
Kayal et al.	Osteosarcoma	MRI images of 55 patients	Nine segmentation algorithms including clustering and ML methods	Identified SLIC superpixels and fuzzy c-means clustering as effective segmentation techniques for osteosarcoma tumors in diffusion-weighted MRI.
Anisuzzaman et al.	Osteosarcoma	Children's Medical Center histology dataset	Transfer learning with VGG19 and InceptionV3	Demonstrated deep learning-based malignancy detection with up to 96% classification accuracy using histological images.

Li et al.	Osteosarcoma	Serum metabolomic dataset (96 samples)	Machine learning classifiers including RF, SVM, and logistic regression	Random Forest achieved the highest classification performance with 95% accuracy and AUC of 0.99 for osteosarcoma diagnosis.
Hermessi et al.	Soft Tissue Sarcoma	Cancer Imaging Archive MRI dataset	Deep feature learning with transfer learning radiomics	Proposed fusion-based feature learning approach improving classification of liposarcoma and leiomyosarcoma tumors.
Peeken et al.	Soft Tissue Sarcoma	MRI radiomics dataset	Radiomics feature extraction and predictive modeling	Developed MRI-based radiomics models for differentiating low-grade and high-grade sarcoma tumors.
Bansal et al.	Osteosarcoma	942 histology images	Customized Convolutional Neural Network	Designed a CNN model for multiclass classification of tumor types with improved accuracy (93.39%) compared to traditional ML models.
Zhang et al.	Soft Tissue Sarcoma	CT and MRI dataset (TCIA)	Transfer learning using Inception-V3 CNN	Developed deep learning models to predict tumor grade and lung metastasis from imaging data.

Blackledge et al.	Soft Tissue Sarcoma	Multi-parametric MRI dataset	Supervised machine learning segmentation	Segmented heterogeneous tumor tissue patterns after treatment using MRI-based analysis.
Chen et al.	Ewing Sarcoma	SEER dataset (2332 patients)	Random Forest, SVM, neural networks	Predicted five-year survivorship with machine learning models, with Random Forest showing the best predictive performance.
D'Acunto et al.	Osteosarcoma	Microscopic cell images	Faster R-CNN with Inception-ResNet v2	Developed automated osteosarcoma cell detection system achieving classification accuracy of approximately 97%.
Li et al.	Osteosarcoma	Gene expression datasets (GEO)	Random Forest and Artificial Neural Network	Identified nine potential diagnostic biomarkers and developed a predictive osteosarcoma diagnosis model.
Pan et al.	Osteosarcoma	H&E histological image dataset	Vision Transformer with noise-reduction feature fusion	Proposed NRCA-FCFL architecture to address noisy histology images and improve classification accuracy.
Tang et al.	Osteosarcoma	MRI dataset (4000 images)	Attention-based deep learning segmentation model	Developed OMSAS segmentation system to assist clinical diagnosis

				with improved segmentation accuracy.
Liu et al.	Osteosarcoma	SEER dataset	DeepSurv and Cox survival models	Developed survival prediction framework for cancer-specific survival prediction in osteosarcoma patients.
Deepak et al.	Bone Sarcoma	TCIA osteosarcoma dataset	Ensemble machine learning model with feature extraction	Achieved high tumor classification accuracy of 98.5% using combined ensemble classifiers.
Ho et al.	Osteosarcoma	Whole slide histopathology images (3134 WSIs)	Deep Multi-Magnification Network	Estimated tumor necrosis ratio and predicted survival outcomes using automated histopathological analysis.
Li et al.	Osteosarcoma	SEER clinical dataset	Deep Belief Network	Developed clinical decision-support system for survival prediction using deep learning representation learning.
Vezakis et al.	Osteosarcoma	Public histopathology dataset	MobileNetV2 and EfficientNet architectures	Showed lightweight networks outperform larger models for osteosarcoma detection with accuracy around 91%.

Bai et al.	Osteosarcoma	SEER dataset	Machine learning models with SHAP interpretability	Developed interpretable model predicting distant metastasis risk in osteosarcoma patients.
Li et al.	Osteosarcoma	SEER dataset (1094 patients)	XGBoost, Random Forest, Gradient Boosting	Predicted lymph node metastasis risk and developed an online risk prediction calculator.
Jeong et al.	Osteosarcoma	PET imaging dataset (70 patients)	Machine learning with PCA feature reduction	Predicted chemotherapy response using PET texture features with SVM achieving highest accuracy (85.7%).
Wilke et al.	Soft Tissue Sarcoma	Chest X-ray and CT dataset	CNN-based metastasis detection	Developed automated detection of pulmonary metastasis with sensitivity of 94% and overall accuracy of 91%.
Foersch et al.	Soft Tissue Sarcoma	Histopathology slides (506 samples)	DenseNet121 deep learning architecture	Improved diagnostic accuracy for sarcoma subtype classification and survival prediction.
Chaber et al.	Ewing Sarcoma	FTIR spectroscopy dataset	Random Forest and SVM	Predicted treatment outcomes using spectral analysis with accuracy exceeding 92%.

Meem et al.	Osteosarcoma	H&E histology dataset	Transfer learning with EfficientNet, ResNet, InceptionResNet	Achieved highest accuracy (93.29%) using InceptionResNetV2 model.
Lv et al.	Osteosarcoma	MRI dataset (204 patients)	Edge-enhanced AI segmentation framework	Improved tumor segmentation performance with Dice coefficient of 0.949.
Gou et al.	Osteosarcoma	Histopathology dataset	Active learning with GAN-assisted classification	Developed multimodal classification system achieving high performance (AUC 0.995) while reducing annotation cost.

The summarized literature presented in Table 2 shows that AI-based sarcoma detectors have evolved very fast. Applying deep learning models to histopathological images has received many studies because these images have rich morphological details that can be used to accurately identify the type of tumor. Radiomics based solutions are also receiving much attention because they offer quantitative descriptors that describe tumor heterogeneity and growth patterns. Moreover, radiological imaging systems with clinical data and machine learning algorithms have also demonstrated potentially productive outcomes in the areas of diagnostic accuracy and predicting patient survival.

Table 3. Challenges and Limitations in AI-Based Cancer Detection Systems

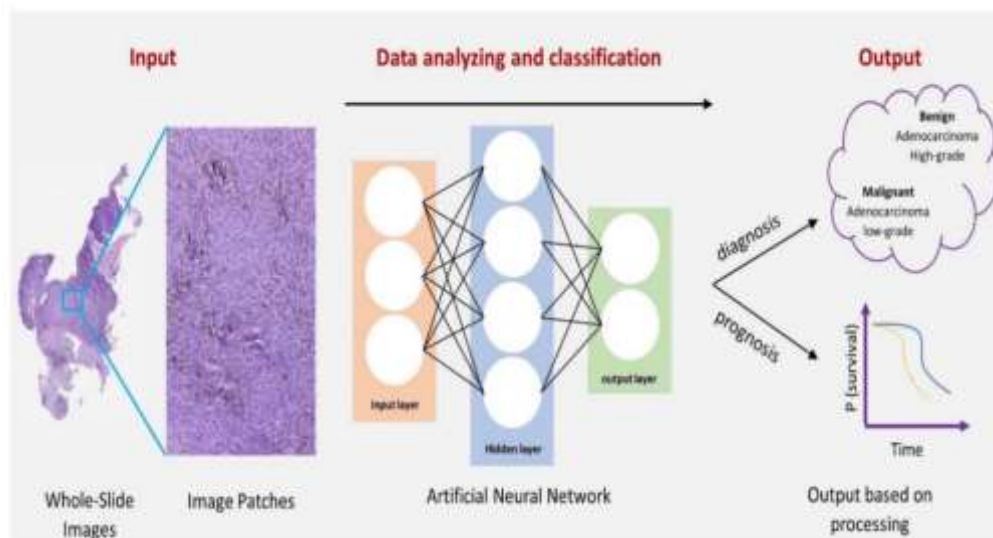
Challenge	Detailed Description	Root Cause	Impact on Detection Systems	Possible Mitigation Strategies
Limited Medical Datasets	AI models require large annotated datasets, but rare cancers such as osteosarcoma and soft tissue sarcoma often have limited imaging data available.	Low disease incidence and restricted access to clinical datasets.	Small datasets reduce model robustness and increase the risk of overfitting.	Data augmentation, synthetic data generation using GANs or diffusion models, and multi-institution dataset sharing.

Data Imbalance	Medical datasets frequently contain far more normal images than tumor samples.	Natural imbalance between healthy and diseased populations.	Models become biased toward majority classes and miss rare tumor cases.	Oversampling, SMOTE, class-weighted loss functions, and balanced dataset construction.
Model Interpretability	Deep learning models often act as black boxes, making it difficult to explain how predictions are generated.	Complex neural network architectures with millions of parameters.	Clinicians may not trust AI predictions without transparent reasoning.	Explainable AI techniques such as Grad-CAM, SHAP, LIME, and attention-based visualization.
Computational Complexity	Training large deep learning models requires significant computational power and memory.	High-resolution medical images and large neural networks.	High hardware cost and longer training times hinder clinical deployment.	Model optimization, lightweight architectures, pruning, and distributed computing.
Cross-Institution Variability	Imaging protocols vary across hospitals, scanners, and acquisition techniques.	Differences in imaging equipment, settings, and preprocessing standards.	Models trained on one dataset may perform poorly on data from other hospitals.	Domain adaptation, transfer learning, and multi-center training datasets.
Annotation Cost	Medical image labeling requires expert radiologists or pathologists, making the annotation process slow and expensive.	Specialized medical expertise required for accurate labeling.	Dataset creation becomes costly and time-consuming.	Active learning, semi-supervised learning, and automated annotation tools.
Ethical and Privacy Concerns	Medical datasets contain sensitive patient information that must comply with privacy regulations.	Healthcare data protection laws such as HIPAA and GDPR.	Strict regulations limit data sharing between institutions and researchers.	Federated learning, secure multiparty computation, and anonymization

				techniques.
Tumor Heterogeneity	Tumors vary significantly in morphology, size, texture, and stage across patients.	Biological variability and different cancer subtypes.	Models struggle to capture all tumor variations, reducing prediction accuracy.	Multimodal learning combining imaging, genomic, and clinical data.
Image Noise and Artifacts	Medical images may contain noise or artifacts due to imaging equipment or staining procedures.	Scanner limitations, staining variability, and imaging conditions.	Noise interferes with feature extraction and reduces classification accuracy.	Image preprocessing, noise reduction filters, and normalization techniques.
Clinical Validation Gap	Many AI models are validated only on experimental datasets and not in real clinical environments.	Limited clinical trials and real-world testing.	AI models may perform differently in actual hospital workflows.	Prospective clinical trials, multi-center validation, and regulatory evaluation.

Although the AI-based cancer detection systems have demonstrated impressive advancement, a number of technical and clinical issues are still unsolved. The lack of annotated medical datasets, especially with rare cancer types like sarcoma and osteosarcoma is one of the most critical concerns. To perform well, deep learning models often need vast amounts of labelled data, which is frequently unattainable in medical image tasks, and in any case, may need a team of expert radiologists or pathologists to do so. Moreover, the models of deep learning are often accused of being uninterpretable and it may impede the implementation of the models in clinical practice where they require transparency and reliability. The differences in imaging protocols applied in different healthcare institutions may also influence the generalizability of models, as working with AI-based systems may be a challenging task to apply in practice. Overcoming these obstacles will be the key to the successful implementation of AI technologies in the everyday cancer diagnostics.

Figure 8. Deep learning methods for sarcoma detection using histopathological image analysis.



Source: Ahmed, Alhassan Ali, et al. "Deep Learning Approaches in Histopathology." *Cancers*, vol. 14, no. 21, 2022.

Figure 8 represents a deep learning structure that is commonly implemented in histopathology cancer diagnosis. This technique consists of a sequence of separate patches of whole-slide images that are displayed through artificial neural networks to identify and classify features in an automated fashion. These image patches are passed through the neural network to identify tumors patterns and predict their diagnoses. Such AI-based pipelines are also used in digital pathology, and automated image processing may assist clinicians to make cancer diagnoses better and more consistent.

4. DISCUSSION

As the analysis of the reviewed literature has shown, there is a sharp step toward the implementation of the techniques of artificial intelligence and machine learning to recognize and predict sarcoma and osteosarcoma. The possible computational techniques have demonstrated promising outcomes in identifying the presence of tumors, the tumor type and the survival outcome basing on medical images and clinical data. Radiomics-based technology in combining MRI and diffusion-weighted imaging (DWI) technology has proved that it has a high potential of providing quantitative tumor data that can be utilized in addressing the segmentation and classification problem. Popular deep learning models that have been trained to learn hierarchical representations of medical images and perform automated tumor detection and classification are convolutional neural networks (CNNs), dense net models, and generative adversarial networks (GANs). As well, the predictive models of tumor classification have been demonstrated to have high predictability rates using machine learning algorithms, such as the Random Forest, the Support Vector Machines (SVM), the Logistic Regression, and the XGBoost as well. Transfer learning is now an important method to improve the accuracy of models, especially in medical imaging where only a limited number of examples of annotated data exist. Scholars have been in a position to fine-tune the pre-trained CNN architectures, such as VGG19, Inception-v3, and ResNet, to enhance the diagnostic quality of sarcoma detection problems. Also, ensemble learning techniques and multimodal information integration techniques have been used to predictively improve accuracy in imaging data, radiomic features, and clinical records to enhance predictive accuracy. Despite these advances, several challenges are placed on the path to the realization of the effective AI-based diagnostic systems. The lack of access to

annotated medical data, institutional disparities in the imaging processes, the impossibility of predictive features extraction in histopathological images, and barriers to ensuring the generalizability and interpretability of the models are these problems. These disadvantages will be one of the keys to the effective implementation of the AI-based systems of cancer detection into a real clinical scenario.

Table 4. Summary of Key Findings from the Discussion Investigations

Investigation	Research Objective	Methods / Algorithms Used	Key Findings	Limitations Identified
Investigation 1	Identify methods that effectively predict the presence or absence of sarcoma and osteosarcoma	Radiomics, CNN, DenseNet, GAN, Random Forest, SVM, Logistic Regression, XGBoost, Faster R-CNN	Radiomics combined with MRI and DWI imaging showed strong segmentation accuracy. CNN-based architectures demonstrated high classification performance for tumor detection. Ensemble learning improved prediction reliability.	Performance varies depending on dataset size, imaging modality, and model architecture
Investigation 2	Evaluate the effectiveness of transfer learning for improving AI-based tumor detection	Transfer learning with pre-trained CNN models such as VGG19, Inception-v3, ResNet	Transfer learning improved classification accuracy when training datasets were limited. Fine-tuned CNN models successfully extracted disease-specific features from medical images.	Domain adaptation challenges due to differences between medical images and natural image datasets

Investigation 3	Identify imaging modalities that provide the highest prediction accuracy	MRI, CT scans, histopathological images combined with machine learning models	Random Forest achieved high predictive performance with 95% accuracy and 0.99 AUC in classification tasks. CNN models showed strong performance in predicting tumor grading and metastasis.	Differences in image quality and acquisition protocols may affect prediction results
Investigation 4	Identify challenges in constructing AI-based predictive models	Feature extraction techniques, radiomics, deep learning models, survival prediction algorithms	Key challenges include feature selection complexity, data imbalance, and model optimization issues. Large annotated datasets are required to train deep learning models effectively.	Limited datasets for rare cancers, high annotation cost, and difficulties in generalizing models across institutions

5. FUTURE DIRECTIONS

The rapid rate of development of artificial intelligence and machine learning tools has offered new opportunities to improve the diagnosis and detection of sarcoma and osteosarcoma. However, despite the promising outcomes of the current AI-specific diagnostic tools in the field of medical imaging and the classification of tumors, there is a possibility that some of the newer tools could enhance the effectiveness and precision of the existing tools and the number of cases of their implementation into clinical practice. It is expected that the future research will take into account the integration of more complex neural network pieces, models of multimedia data integration and real-time diagnostic systems that could be applicable in assisting practitioners to conduct healthcare. Furthermore, the development of intelligent decision-support systems that will combine the imaging, genomic, and clinical data will be essential in improving the early diagnosis and treatment plans per person. However, the ethical challenges related to the application of AI in healthcare are also model interpretability, transparency, and privacy that also should be taken into account. Such problems and the need to employ the new methods of computation will be crucial to the development of efficient and diagnostic sarcoma-monitoring systems. The following subsections highlight some of the good research directions that would be significant in AI-based cancer detection and clinical decision support.

5.1 Deep Learning Architectures with attention

It is suggested that the evolution of attention mechanisms into the deep learning structure, that is, convolutional neural networks (CNNs), is one of the potential methods that could improve the process of sarcoma detection. Attention mechanisms enable the neural

networks to focus on most interesting aspects of the medical images and ignore the rest of the information that is not important. This skill is particularly important in medical imaging since the tumors may be reflected in the form of minute variations in tissues structures. Attention models such as Vision Transformers (ViT) and attention directed CNN models can improve the state-of-the-art in the field of tumor localization and segmentation by focusing on diagnostic relevant features. Combining attention systems and the existing CNN models might enable researchers to develop more effective diagnostic tools that would be able to identify early-stage sarcoma and osteosarcoma more precisely.

5.2 Multimodal Graph Neural Networks Data Integration.

The alternative potential research is the multimodal adoption of medical data through Graph Neural Networks (GNNs). Ordering a variety of data types, including radiologic images, histopathologic slides, genomic information, and clinical records of the patient are often required to detect sarcomas. The standard paradigm of classic machine learning operations treats each of these data sets individually and that may limit its predictive ability. GNNs are useful in that they can be used to model the relationship between other data modalities by modeling them as interconnected nodes within a graphical format. Tumor progression is an event that can be approached with the help of GNN-based models that provide a deeper insight into the event and improve the quality of the diagnosis by integrating both the imaging features, molecular biomarkers, and clinical data into a single analysis model.

5.3 Edge device-based real-time diagnostics systems based on AI.

The other great way in the future is the development of real-time diagnostic tools that can be optimized to edge computing platforms. The currently existing AI-based diagnostic systems typically require high-performance computing systems, which limits the functionality of such a system to be applied in a clinical environment where real-time results are required. It is also possible to run deep learning models on medical devices and process medical images in real time during a diagnostic procedure with the use of the edge AI systems. An example of this situation is the use of diagnostic equipment that could be transported and have built-in AI algorithms, which could analyze imaging data in real-time and provide clinicians with real-time information about the characteristics of tumours. Such a system can help to reduce the diagnostic delay significantly, in addition, help to adhere to the timely intervention strategy, particularly in the specified scenario when the available resources are limited.

5.4 Medical Diagnostics Ethics and Explainable AI.

As the number of AI systems implemented in the clinical workflow increases, transparency and trust in AI-based decisions should be assured. Majority of deep learning models are black boxes making it difficult to clinicians to explain the process of diagnostic predictions. Explainable Artificial Intelligence techniques (XAI) methods are created to address this problem by providing interpretable explanations of predictions of a model. Visualization, saliency maps, and gradient-based approaches to attribution are only some of the techniques that can bring out image regions that can be used to make diagnostic decisions, and in such a manner enable clinicians to challenge AI-based predictions. In addition to the interpretability, other ethical aspects must also be taken into consideration, i.e. the minimization of bias, privacy of patient data, and adherence to rules must be considered to ensure that AI technologies in healthcare are also implemented responsibly. The construction of reliable AI systems in the detection of cancer will require developments of XAI and ethics AI systems.

6. CONCLUSION

This review paper is a rigorous analysis of the artificial intelligence and machine learning techniques, which are applied in detecting and diagnosing sarcoma and osteosarcoma. A wide range of computational methods, including radiomics-based methods, conventional machine learning methods, and the latest deep learning architectures, have been considered in the paper as far as the interpretation of medical imaging and clinical data is concerned. The findings of the literature review indicate that the AI-based diagnostic systems have already been found to possess enormous potential in terms of improving the accuracy and efficiency of the tumor detection procedure. The traditional neural network and the transfer structure have proven to have a positive performance with regard to identifying the patterns of tumors in MRI, CT, and histopathology image identification. It has also been through radiomics based strategies that have enabled the derivation of quantitative imaging features that can be used to assist in the classification of the tumors and also in prognosis. The other important feature of the analysis is that there is a growing importance of the need to integrate different types of data, i.e. imaging data, clinical records, and genomic data to formulate significantly more complex diagnostic structures. Despite the encouraging outcomes presented in the literature, the implementation of AI-based diagnostic systems in clinical practice still has a number of problems. These include the lack of annotated datasets of rare cancers, uncertainty of imaging protocols between institutions, and the problem of model interpretability and ethics. Future research must address the shortcoming of datasets, develop explainable artificial intelligence models, and integrate intelligent such as attention and graph neural networks and networks.

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