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Automatic Bone Cancer Detection _A Comprehensive Survey

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***Abstract*— Bone cancer is a complicated and diverse category of cancers that can start in the bone (primary bone cancer) or move to the bones from other regions of the body (secondary bone cancer). For successful treatment and better patient outcomes, bone cancer must be identified early and properly diagnosed. This survey paper provides a review of bone cancer detection methods, encompassing both primary and secondary bone cancer. It covers the many primary bone cancers, such as osteosarcoma, Ewing sarcoma, chondrosarcoma, and chordoma, emphasizing their clinical characteristics, prevalence, and diagnostic difficulties. Additionally, the paper explores secondary bone cancer, focusing on common primary cancers that metastasize to the bones, such as breast cancer, lung cancer, prostate cancer, and kidney cancer. Various diagnostic techniques, including conventional imaging methods, emerging imaging modalities, biomarkers, radiomics, machine learning, and genetic markers, are examined in detail. The limitations, advancements, and future directions in bone cancer detection are also discussed. The goal of this survey report is to improve early detection, accurate diagnosis, and individualized treatment options for bone cancer. It serves as a significant resource for researchers, physicians, and healthcare professionals concern with the diagnosis and management of bone cancer.**

***Index Terms*— osteosarcoma, Ewing sarcoma, chondrosarcoma and chordoma ,machine learning, genetic markers.**

I. INTRODUCTION

Today, medical area has witnessed rapid growth of automation technology. Still, diagnosis system is not adequate for increased variety of diseases. Cancer disease spread across the world and it is beyond the control. Thus, bone cancer is becoming common and its detection is complicated due to its complex features. WHO report states that cancer is the reason for death of 9.2 million people in the year 2020(WHO 2020). Primary bone cancer cases are found to be 0.8%. These observations show that bone disease is widespread throughout the world, just like any other pandemic. Therefore, bone cancer research is essential to saving the lives of millions of individuals.

A. Overview of bone formation

The connective tissue is made up of cells and extracellular matrix makes up bone and cartilage. Osteoblasts, osteocytes, and osteoclasts are the three primary types of bone cells. Osteoblasts are a type of bone-synthesising

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cell that gradually transforms from osteoid into tougher bone. Osteoblasts, which develop into osteocytes throughout the process of bone formation, are buried in the bone matrix. These osteocytes are more frequently found in mature bone. Osteoclasts are essential for bone remodeling and healing. Large, multinucleated cells called osteoclasts are present on the surfaces of bones. A robust, flexible, and semi-rigid supporting tissue, cartilage is made up of chondroblasts and chondrocytes.

B. Types of bone cancer

Here is a detailed discussion of the types of bone cancer, including primary and secondary bone cancer:

a. Primary Bone Cancer:

Primary bone cancer originates in the bone itself and includes various subtypes.

1. Osteosarcoma:

The most prevalent primary bone cancer, osteosarcoma, primarily affects children and young people. Usually, the long bones in the arms and legs are affected. [Mirabello L, et al. (2009)].

2. Ewing sarcoma:

Ewing sarcoma primarily affects children and adolescents. It commonly occurs in the pelvis, thigh bones, and chest wall. Ewing sarcoma is characterized by a specific genetic abnormality called the EWSR1-FLI1 fusion gene. Symptoms may include localized pain, swelling, and bone tenderness. Ewing sarcoma is relatively rare, accounting for about 1% of childhood cancers[Grier HE, et al. (2003)].

3. Chondrosarcoma:

Chondrosarcoma arises from cartilage cells. It typically occurs in older adults and develops in the bones of the pelvis, upper legs, and shoulders. Chondrosarcoma is characterized by slow growth and can be low-grade or high-grade. Symptoms may not be evident until the cancer reaches an advanced stage. It is the second most common primary bone malignancy after osteosarcoma[Gelderblom H, et al. (2018)].

4. Chordoma:

Chordoma is a rare type of bone cancer that develops from remnants of the notochord, a structure present during early fetal development. It commonly affects the base of the skull or the bones of the spine. Chordomas are typically slow-growing but can be locally aggressive. Symptoms may include pain, neurological deficits, and bowel or bladder dysfunction. Chordoma accounts for approximately 1-4% of primary malignant bone tumors[: McMaster ML, et al. (2012)].

b. secondary bone cancer

When cancer cells from other parts of the body migrate to the bones, it results in secondary bone cancer, also known as metastatic bone cancer.

1. Breast cancer:

Breast cancer frequently metastasizes to the bones, particularly the spine, ribs, and long bones. Bone metastases in breast cancer may cause bone pain, fractures, and other complications. The paper flow is introduction, different methods of automatic bone cancer detection, datasets, discussion and future scope with concluding remark. Figure 1 shows the simple difference between normal bone and Cancer bone.

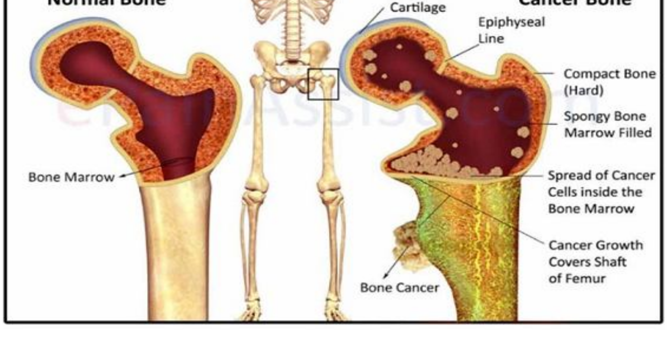

Figure 1: simple example of bone cancer [16]

II. Methods Of Bone Cancer Detection Using Machine Learning

A. Deep Learning:

Deep learning techniques have shown promising results in various medical applications, including the detection and diagnosis of bone cancer. Here are a few deep learning techniques commonly used for bone cancer detection:

a. Convolutional Neural Networks (CNNs):

CNNs are frequently employed for image classification applications, including the study of medical images. CNNs can examine diagnostic pictures like X-rays, CT scans, or MRI scans in the event of bone cancer detection. The network becomes trained to automatically identify the images' pertinent attributes and categorize them as either healthy or malignant.

b. Transfer Learning:

Transfer learning involves leveraging pre-trained deep learning models that have been trained on large datasets for general image recognition tasks. These models, such as VGGNet, ResNet, or Inception, have learned useful features from vast amounts of data. By fine-tuning these models on a smaller dataset of bone cancer images, the network can adapt and learn to detect specific patterns indicative of bone cancer.

c. Recurrent Neural Networks (RNNs):

RNNs are commonly used for sequential data analysis, such as time series or text data. In the context of bone cancer detection, RNNs can be employed to analyze sequential data, such as patient medical records or longitudinal imaging studies. By capturing temporal dependencies, RNNs can help in predicting or detecting cancer progression.

d. Generative Adversarial Networks (GANs):

GANs are composed of a generator and a discriminator network, which work together in a competitive manner. GANs can be utilized for generating synthetic medical images that closely resemble real bone cancer images. This can help augment limited datasets, create synthetic data for training, or aid in data augmentation techniques.

e. Attention Mechanisms:

Attention mechanisms are designed to improve the focus on important regions or features within an image. They can be incorporated into CNN architectures to selectively emphasize regions in medical images that are more informative for bone cancer detection. This can enhance the performance of deep learning models by directing their attention to relevant areas. Below table 1 contains the deep learning techniques for bone cancer detection, along with their advantages and disadvantages:

B. Transfer learning: Using pre-trained models on huge datasets, transfer learning is a powerful technique for improving the performance of models in new, related tasks with minimal labeled data. Transfer learning has various uses for automatic bone cancer screening, including:3. Domain, 2. Fine-tuning, and 1. Feature Extraction.5. Knowledge Distillation, 4. Multi-Task The table 2 below lists the various transfer learning techniques along with their benefits and drawbacks.

TABLE I: DIFFERENT DEEP LEARNING TECHNIQUES

Deep Learning Technique	Description	Advantages	Disadvantages
Convolutional Neural Networks (CNNs)	CNNs analyze medical images (e.g., X-rays, CT scans, MRI scans) to automatically extract features and classify them as cancerous or healthy.	1.High accuracy in image classification tasks. Automatically learns relevant features from images without manual feature engineering. 2.Can handle high dimensional image data effectively.	1.Requires a large amount of labeled data for training. 2.Prone to overfitting if the dataset is small or imbalanced. 3.Computationally intensive, requiring powerful hardware and longer training times.
Transfer Learning	Leveraging pre-trained models (e.g., VGGNet, ResNet, Inception) trained on general image recognition tasks and fine-tuning them on bone cancer images for specific pattern detection.	1. Allows for effective use of pre-existing knowledge from large-scale datasets. 2. Reduces the need for large labelled datasets by leveraging pre-trained weights.	1.The pre-trained model might not be specifically optimized for bone cancer detection, requiring careful fine-tuning. 2.Fine-tuning process requires expertise to balance the transfer of learned knowledge and adapt to the specific bone cancer detection task.

Recurrent Neural Networks (RNNs)	RNNs analyze sequential data (e.g., patient records, longitudinal imaging studies) to capture temporal dependencies and aid in predicting or detecting cancer progression.	1.Captures temporal dependencies and patterns in sequential data. 2.Can incorporate longitudinal patient data for personalized cancer progression analysis. 3. Suitable for time series analysis of patient data over time.	1.RNNs can suffer from vanishing or exploding gradients, affecting training and performance. 2.Sequential data may require preprocessing and normalization to handle missing values and variable-length sequences. 3.Computationally intensive, especially with large sequences and complex architectures.
Generative Adversarial Networks (GANs)	GANs can generate synthetic medical images resembling real bone cancer images, which can augment limited datasets or aid in data augmentation techniques.	1.Can generate synthetic images that mimic real bone cancer images, expanding the dataset for training. 2.Augments limited datasets, allowing for improved model generalization. 3.Helps in data augmentation, reducing over fitting and improving model robustness.	1. Generating high-quality and realistic synthetic images can be challenging. 2. Requires careful evaluation and validation of the generated synthetic images' quality and similarity to real images.
Attention Mechanisms	Incorporating attention mechanisms into CNN architectures to selectively emphasize informative regions in medical images for bone cancer detection.	1.Selectively emphasizes relevant regions in medical images, improving accuracy. Can help in localizing cancerous regions within images.	1.Complex attention mechanisms may require additional computational resources. 2.Designing effective attention mechanisms may require expertise and experimentation.

TABLE II: TRANSFER LEARNING METHODS.

Transfer Learning Method	**Description**	**Advantages**	**Disadvantages**
Feature Extraction	Use pre-trained models as feature extractors, keeping the weights frozen, and adding task-specific layers	1. Leveraging pre-trained models for efficient feature extraction 2. Faster training and inference as only the added layers are trained 3. Effective when pre-trained models capture relevant general visual features	1.Limited adaptability of pre-trained features to the specific bone cancer detection task
Fine-tuning	Update some or all of the pre-trained model's weights during training to adapt to the bone cancer detection task	1. Ability to learn task-specific features while retaining knowledge from pre-training. 2. Potential for improved performance compared to feature extraction alone.	1. Requires more labeled data for fine-tuning 2. Prone to overfitting when the labeled data is limited
Domain Adaptation	Bridge the domain gap between pre-training and the target domain using techniques like adversarial training	1. Adapt the model to the target domain with different data distributions	1. Requires a large amount of labeled data from the target domain to achieve effective domain adaptation
		2. Address the limitations caused by domain shift	2. Complex to implement and may introduce additional computational overhead
Multi-Task Learning	Train the model to perform multiple related tasks simultaneously, leveraging shared representations	1. Shared representations improve model generalization and robustness 2. Can help in joint learning of tasks that may have shared underlying features	1. Requires additional labeled data and annotations for the related tasks 2. Increased model complexity and potential interference between the tasks
Knowledge Distillation	Transfer knowledge from a large, well-performing model to a smaller, lightweight model	1. Enables efficient inference on resource-constrained devices 2. Compression of a large model into a smaller model without significant performance degradation	1. Knowledge transfer may result in some loss of accuracy compared to the teacher model 2. Relies on the availability of a well-performing teacher model and the need for a separate training process.

C. Ensemble Learning:

There are three methods for ensemble learning in automatic bone cancer detection: Voting Ensemble, Bagging, Boosting. Below table 3 summarizing the methods for ensemble learning in automatic bone cancer detection, along with their advantages, disadvantages.

D. Explainable AI (XAI)

There are three methods for explainable AI in automatic bone cancer detection: Feature Importance, Rule Extraction, Model Visualization. Below table 4 is summarizing the methods for explainable AI in automatic bone cancer detection, along with their advantages, disadvantages.

TABLE III: ENSEMBLE LEARNING METHODS

Ensemble Learning Method	Description	Advantages	Disadvantages
Voting Ensemble	Multiple independent models are trained, and their predictions are aggregated through voting or averaging to obtain the final prediction.	Reduces the impact of individual model biases and errors.	Limited adaptability of pre-trained features to the specific bone cancer detection task.
Bagging	Multiple models are trained on subsets of the original training data created through bootstrapping, and their predictions are aggregated to obtain the final prediction.	Reduces overfitting by introducing diversity in the training process.	Requires additional computational resources for training and inference.
Boosting. (Zhang et al.2021.)	A sequence of models is trained, with each subsequent model focusing on correcting the mistakes of the previous models. The predictions of all models are combined to obtain the final prediction.	Improves accuracy by iteratively adjusting the models to focus on challenging samples.	Prone to overfitting when the labeled data is limited.

TABLE IV METHODS OF EXPLAINABLE AI (XAI)

XAI Method	Description	Advantages	Disadvantages
Feature Importance Bilgic et al. (2022).	Identifies influential features or regions in the input data that significantly contribute to the model's predictions.	1.Provides insights into the specific characteristics of bone images that are indicative of cancer. 2. Helps in identifying the most relevant features for bone cancer detection. 3. Facilitates model validation and trust-building among medical professionals.	1. May not capture complex interactions between features. 2. Does not necessarily provide causal relationships between features and predictions. 3. Limited to feature-level interpretation and may not capture spatial relationships in images.
Rule Extraction	Distills the decision logic of complex models into human-readable rules or if-then statements.	1. Provides transparent and interpretable rules for bone cancer diagnosis. 2. Helps in understanding the specific criteria or conditions used by the model for classification. 3.Enables medical professionals to validate and interpret the decision-making process.	1.May result in simplified rules that do not capture the full complexity of the model. 2. Extraction of rules may be challenging for deep learning models due to their complex structures. 3. Rule extraction techniques may not scale well with large and high-dimensional datasets.
Model Visualization Li, M., et al. (2021).	Provides visual representations of the internal workings of the machine learning model.	Facilitates understanding of the learned representations, feature activations, and decision boundaries of the model. 2. Helps in visualizing similarities and relationships between bone images. 3. Identifies important regions or pixels that contribute to the model's predictions.	1. Visualization techniques may be subjective and require interpretation. 2. Visualizations may not provide a comprehensive understanding of the entire model. 3. Interpretability may vary depending on the complexity of the visualization technique used.

E. Few-Shot Learning:

Few-shot learning is a machine learning approach that aims to address the challenge of learning from limited labelled data. In the context of bone cancer detection, few-shot learning methods can be utilized to develop models that can accurately classify bone cancer instances with only a small number of labelled examples. Here, table 5 of a few popular methods used in few-shot learning for bone cancer detection, along with relevant citations for further reading.

TABLE V FEW-SHOT LEARNING METHOD

Sr. No.	Few-Shot Learning Method	Advantage	Disadvantage
1	Meta-learning	1. Enables fast adaptation to new tasks	1. Requires a large number of related tasks for effective meta-training
2	Metric-based approaches	1. Learns a discriminative distance metric for effective classification	1. May struggle with high-dimensional feature spaces
3	Data augmentation	1. Increases the available labelled data for training	1. Augmented samples may not accurately represent the true distribution of the bone cancer data
4	Generative models Qiao et al. in 2018 [4]	1. Can generate additional samples to augment the labelled dataset.	1. Generated samples may lack variability and may not cover the full range of bone cancer instances

III. DATASET

Bone cancer detection is a crucial area of medical research and technology development that involves the use of various datasets to train and evaluate algorithms for accurate diagnosis and assessment. Below is the table summarizes the common datasets with other details.

TABLE VI: DIFFERENT DATASETS OF AUTOMATIC BONE CANCER DETECTION

SrNo.	Dataset Name	Description	Modality(s)	Number of Samples	Availability
1	Osteosarcoma Dataset [15]	Histopathology images of osteosarcoma bone tumors	Histopathology	500	Available upon request
2	RSNA Bone Age	Hand X-ray images for bone age assessment	X-ray	12,611	Available through RSNA Radiology AI Sandbox
3	MURA	Upper extremity X-ray images for abnormality detection	X-ray	14,863	Available through Stanford ML Group
4	DDSM Calcification	Mammogram images with calcification clusters	Mammography	49	Digital Database for Screening Mammography (DDSM)
5	NIH Chest X-rays	Chest X-ray images for common thoracic diseases	X-ray	112,120	National Institutes of Health (NIH)
6	INbreast	Mammogram images for breast cancer detection	Mammography	410	INbreast Dataset
7	LIDC-IDRI	CT scan images of lung nodules for lung cancer detection	CT scan	1,018	The Cancer Imaging Archive (TCIA)
8	ISIC 2019 Skin Lesion	Dermoscopy images for skin lesion classification	Dermoscopy	25,331	International Skin Imaging Collaboration (ISIC)
9	Brain Tumor MRI	MRI scans of brain tumors for brain cancer detection	MRI	253	Kaggle
10	DeepLesion	CT scan images of various lesions for lesion detection	CT scan	32,735	National Institutes of Health (NIH)

IV. CHALLENGES AND FUTURE DIRECTIONS

Bone cancer detection using machine learning (ML) presents both challenges and promising future directions. One of the primary challenges lies in the availability of high-quality and diverse datasets that encompass different bone cancer types, stages, and imaging modalities. Limited annotated data can hinder the development and generalization of ML models. Furthermore, the interpretability of ML algorithms in bone cancer detection remains a challenge, as the decision-making process of complex models often lacks transparency. Addressing these challenges requires the collaboration of healthcare providers, researchers, and data scientists to curate larger, more representative datasets and develop explainable ML techniques.

In the future, advancements in ML algorithms, such as deep learning architectures, can enhance the accuracy and efficiency of bone cancer detection. Integration of multi-modal imaging, combining various imaging techniques like X-ray, CT, MRI, and PET, can provide a comprehensive understanding of bone tumours. Moreover, the utilization of transfer learning and few-shot learning techniques can mitigate the limitations of limited labelled data by leveraging knowledge from pre-trained models and adapting it to bone cancer detection tasks. Continued research efforts are necessary to develop robust ML algorithms that can assist clinicians in early detection, accurate diagnosis, and treatment planning for bone cancer patients.

V. REMARK

In conclusion, machine learning (ML) techniques have shown promising results in bone cancer detection, aiding in early diagnosis, accurate characterization, and treatment planning. ML models trained on diverse and annotated datasets have demonstrated their ability to analyse different imaging modalities, such as X-ray, CT, MRI, and PET, and assist healthcare professionals in making informed decisions. However, challenges such as limited data availability, interpretability of complex models, and the need for large-scale validation studies still exist. Future research should focus on curating larger and more representative datasets, developing explainable ML algorithms, and integrating multi-modal imaging for a comprehensive understanding of bone tumours. Continued advancements in ML algorithms, including deep learning architectures, transfer learning, and few-shot learning, hold promise for further improving the accuracy and efficiency of bone cancer detection. Collaborations between researchers, clinicians, and data scientists are crucial in advancing the field and translating ML-based bone cancer detection techniques into clinical practice

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