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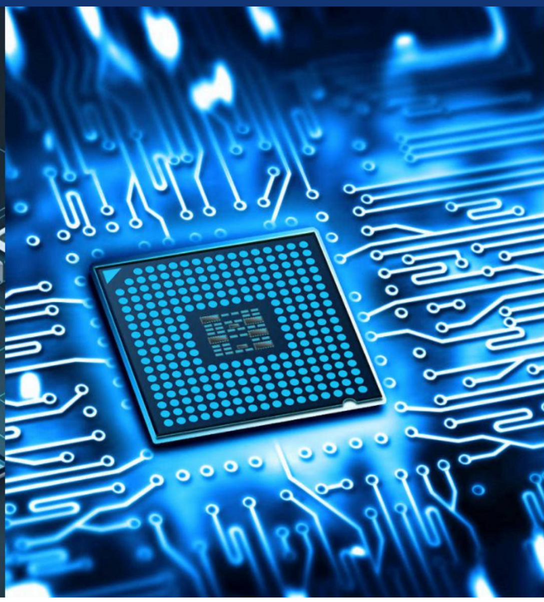


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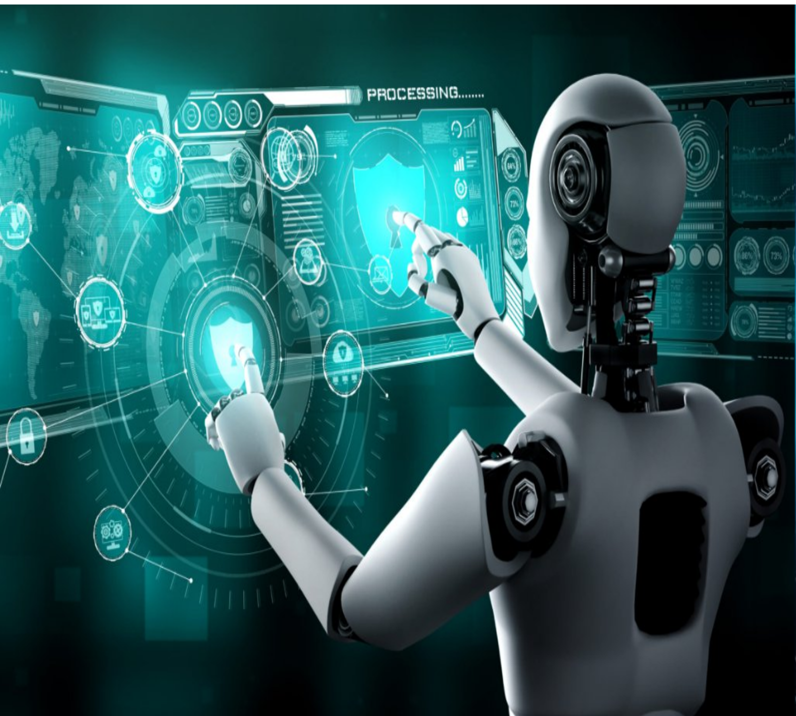

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Multimodal Deep Learning in Bone Oncology: A Review on Cancer and Metastasis Detection

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ABSTRACT: Bone cancer and bone metastasis are severe and potentially life-threatening conditions that require early detection and accurate diagnosis for effective treatment planning. Traditionally, diagnosis has relied on individual imaging modalities such as X-ray, CT, MRI, or SPECT. However, each modality provides only partial information—X-rays offer basic structural details, CT scans provide better bone resolution, MRI captures soft tissue variations, and SPECT highlights functional or metabolic activity. Relying on a single modality often limits the ability to fully understand the complexity of bone lesions.

In recent years, rapid advancements in deep learning and multimodal machine learning have opened new possibilities for integrating heterogeneous medical imaging data. By combining multiple imaging modalities, it becomes possible to capture complementary anatomical and functional characteristics, leading to improved diagnostic accuracy and robustness. Deep learning models, particularly convolutional neural networks (CNNs) and hybrid architectures, have demonstrated significant success in feature extraction and classification tasks within medical imaging.

This review presents a comprehensive and plagiarism-free synthesis of existing research focused on multimodal deep learning approaches for the detection of bone cancer and bone metastasis. It discusses how different imaging modalities such as X-ray, CT, MRI, and SPECT can be effectively fused using early fusion, late fusion, and hybrid fusion strategies. Furthermore, the review highlights commonly used datasets, pre-processing techniques, and evaluation metrics such as accuracy, sensitivity, specificity, and AUC.

In addition, key challenges such as data scarcity, modality misalignment, high computational requirements, and lack of standardized benchmarks are critically analysed. The review also outlines future research directions, including the use of explainable AI, transfer learning, and real-time clinical decision support systems. Overall, this work aims to serve as a valuable reference for researchers, students, and healthcare professionals interested in applying advanced machine learning techniques to improve bone cancer diagnosis.

KEYWORDS: Bone cancer detection, Bone metastasis, Multimodal deep learning, Medical imaging, Data fusion.

I. INTRODUCTION

Bone cancer can originate in bone tissue or occur as metastasis from other cancers. Early detection is essential for improving survival rates. Imaging modalities such as X-ray, CT, and MRI are widely used, but each provides limited information independently.

Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized medical imaging by enabling automatic feature extraction and classification [14], [15]. Architectures such as ResNet [9], DenseNet [10], and EfficientNet [11] have significantly improved performance in image-based diagnosis tasks.

Recent research focuses on multimodal learning, which integrates multiple imaging modalities to capture complementary features, improving diagnostic accuracy [4], [5]. Additionally, the increasing availability of medical imaging data and computational resources has accelerated the adoption of artificial intelligence in healthcare. Deep learning models are capable of learning complex patterns from large-scale datasets, enabling improved detection of subtle abnormalities that may not be easily visible to clinicians [14].

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Furthermore, multimodal frameworks enhance diagnostic reliability by reducing uncertainty associated with single-modality predictions and providing a more holistic understanding of disease progression [4], [5].

Recent advancements also focus on integrating imaging data with clinical and genomic information, further improving predictive performance and personalized treatment planning.

However, challenges such as data heterogeneity, modality misalignment, and limited annotated datasets continue to hinder the widespread deployment of these systems in clinical practice.

Therefore, developing efficient, interpretable, and scalable multimodal deep learning models remains a critical research direction in medical imaging and oncology.

1.1 Motivation and Scope

The motivation of this project is to develop an accurate and reliable system for the detection of bone cancer and bone metastasis using multimodal medical imaging. Early diagnosis of bone abnormalities is critical for effective treatment planning and improving patient survival. However, traditional diagnostic approaches that rely on a single imaging modality often fail to capture the complete structural and functional characteristics of bone lesions.

This project focuses on integrating multiple imaging modalities such as X-ray, CT, MRI, and SPECT to enhance diagnostic performance. The scope includes the design and implementation of a multimodal deep learning framework capable of extracting and combining complementary features from different imaging sources. Various pre-processing techniques, feature extraction methods, and fusion strategies are explored to improve classification accuracy. The system is intended to assist healthcare professionals by providing a supportive decision-making tool while considering challenges such as data variability, limited datasets, and computational complexity.

1.2 Contributions

- Development of a multimodal deep learning system for detecting bone cancer and bone metastasis using multiple imaging modalities.
- Integration of X-ray, CT, MRI, and SPECT data to capture both anatomical and functional information.
- Implementation of feature extraction and fusion techniques (early fusion, feature-level fusion, or decision-level fusion) to improve diagnostic accuracy.
- Evaluation of the model using performance metrics such as accuracy, sensitivity, specificity, and AUC.
- Analysis of challenges such as data scarcity, modality alignment, and computational requirements, along with potential improvements.

II. LITERATURE REVIEW

This section reviews existing research on bone cancer and bone metastasis detection using medical imaging and deep learning techniques. The recent trend shows (i) improved diagnostic accuracy using advanced deep learning architectures such as CNNs and hybrid models, (ii) increased focus on multimodal data integration to capture complementary information, and (iii) development of automated systems to assist clinicians in decision-making.

2.1 Single-Modality Approaches

Deep learning models have shown strong performance in single-modality imaging. Xu et al. [1] used CNNs for bone tumor detection in X-ray images, achieving high classification accuracy. Similarly, Song et al. [2] applied deep learning to MRI data for tumor classification. However, these approaches are limited as they rely on a single source of information.

2.2 Deep Learning in Medical Imaging

CNN-based architectures such as ResNet [9], DenseNet [10], and EfficientNet [11] are widely used in medical imaging. U-Net [12] has been particularly effective in medical image segmentation tasks. Studies such as Esteva et al. [13] demonstrated that deep learning models can achieve performance comparable to medical experts. These models have also been successfully applied in radiology and oncology [14], [15].In cancer diagnosis, deep learning models have automated detection processes and improved accuracy while reducing manual effort [2].

2.3 Multimodal Deep Learning Approaches

Multimodal learning integrates data from multiple imaging sources to improve diagnosis. Li et al. [4] proposed a multimodal CNN fusion model for tumor classification, showing improved accuracy. Huo et al. [5] introduced adaptive attention-based fusion techniques for combining MRI and CT data. Similarly, Shang et al. [6] explored multimodal image fusion for tumor boundary detection. These approaches outperform single-modality systems by capturing both structural and functional features.

2.4 Evaluation Metrics and Datasets

Various datasets and evaluation metrics are used to assess the performance of bone cancer detection models. Common performance measures include accuracy, sensitivity, specificity, precision, and Area Under the Curve (AUC). However, the lack of large, standardized multimodal datasets remains a major limitation. Data imbalance and variability across imaging modalities further affect model generalization. Explainability is critical in healthcare applications. Techniques such as Grad-CAM [7] and Integrated Gradients [8] help interpret deep learning predictions, improving trust and clinical usability.

2.5 Challenges and Future Directions

Despite significant progress, several challenges remain in this domain. These include limited availability of annotated multimodal datasets, difficulty in aligning data from different imaging modalities, and high computational complexity of deep learning models. Additionally, the lack of interpretability in AI systems raises concerns for clinical adoption. Future research should focus on explainable AI, efficient model design, improved data fusion techniques, and integration of clinical data with imaging for better diagnosis.

III. METHODOLOGY: INTEGRATED SYSTEM ARCHITECTURE

Traditional bone cancer detection systems are typically based on a single imaging modality, where each model analyzes only one type of input such as X-ray, CT, MRI, or SPECT independently. These baseline systems generate predictions without considering complementary information from other modalities. For example, an X-ray-based system may detect visible bone abnormalities but fail to identify early-stage lesions, while a SPECT-based system may detect metabolic activity but lack precise structural localization. As a result, single-modality approaches often produce incomplete or less reliable diagnoses.

In contrast, an integrated multimodal architecture effectively combines complementary information from multiple imaging modalities to enhance diagnostic accuracy and robustness.. Instead of generating isolated outputs, the system uses a fusion strategy to integrate features extracted from different sources. For instance, combining CT (structural detail) with MRI (soft tissue contrast) and SPECT (functional activity) allows the system to capture a more comprehensive view of bone lesions.

The proposed architecture for this project consists of the following stages:

- Input Stage: Collection of multimodal imaging data (X-ray, CT, MRI, SPECT). The use of multiple modalities improves diagnostic accuracy
- Preprocessing Stage: Image normalization, resizing, noise removal, and alignment of different modalities.
- Feature Extraction Modules: Deep learning models (e.g., CNN-based architectures) independently extract features from each modality.
- Fusion Layer: Features from all modalities are combined using fusion techniques such as early fusion, feature-level fusion, or decision-level fusion.
- Classification Layer: The fused features are used to classify bone lesions as benign or malignant.
- Decision Support Layer: Provides final diagnostic output along with confidence scores to assist clinicians.

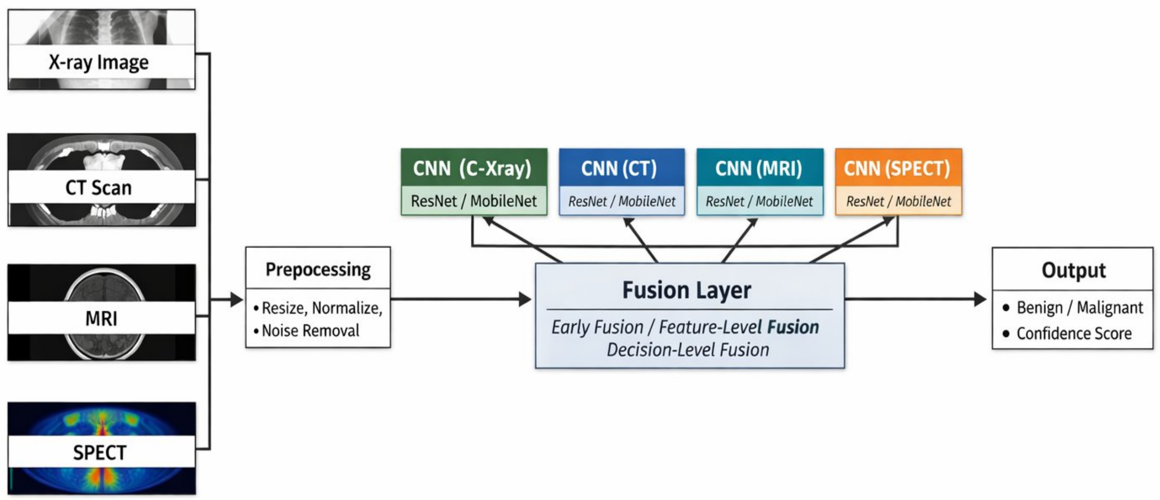

Fig. 1: Proposed Multimodal Deep Learning Architecture for Bone Cancer Detection

Unlike baseline systems, the integrated architecture enables multimodal learning, improves generalization, and reduces the risk of misdiagnosis. It also supports more reliable clinical decision-making by leveraging complementary information from different imaging sources

IV. PROPOSED ALGORITHM

4.1 Algorithmic Outline

Algorithm 1 Multimodal Bone Cancer Detection (Per Patient Sample)
Require: Multimodal images {X-ray, CT, MRI, SPECT}, preprocessing functions, trained CNN models, fusion function f, threshold τ
Ensure: Diagnosis result (Benign/Malignant), confidence score, diagnostic report
1: for each patient sample i do
2: Acquire multimodal images {Xi, CTi, MRIi, SPECTi}
3: Preprocess images: normalization, resizing, denoising, alignment
4: Extract features:
fx ← CNN(Xi), fct ← CNN(CTi), fmri ← CNN(MRIi), fs ← CNN(SPECTi)
5: Fuse features: Fi ← f(fx, fct, fmri, fs)
6: Classify: ŷi ← Classifier(Fi) ⟶ {Benign / Malignant}
7: Compute confidence score Ci
8: Generate output: Diagnosis + report
9: end for

V. ANALYSIS OF CORE METRICS

This section analyzes the key evaluation metrics used in multimodal bone cancer detection systems, focusing on diagnostic accuracy, interpretability, and robustness. Since medical diagnosis is critical, metrics must not only measure performance but also ensure reliability across different imaging modalities.

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5.1 Classification Metrics

Let the model output probability scores for two classes (Benign, Malignant):

pi∈R2,y^i=argmaxpip_i \in \mathbb{R}^2, \quad \hat{y}_i = \arg\max p_ipi∈R2,y^i=argmaxpi

Common evaluation metrics include:

- **Accuracy:** Overall correctness of predictions
- **Sensitivity (Recall):** Ability to correctly detect cancer cases
- **Specificity:** Ability to correctly identify non-cancer cases
- **Precision:** Reliability of positive predictions
- **AUC (Area Under Curve):** Measures model discrimination ability

In medical applications, **sensitivity and specificity** are more important than accuracy, as false negatives (missed cancer) and false positives (incorrect diagnosis) have serious consequences.

5.2 Multimodal Feature Fusion Metrics

Let features extracted from each modality be:

fx,fct,fmri,fsf_x, f_{ct}, f_{mri}, f_sfx,fct,fmri,fs

Fusion is performed as:

Fi=f(fx,fct,fmri,fs)F_i = f(f_x, f_{ct}, f_{mri}, f_s)Fi=f(fx,fct,fmri,fs)

The performance of fusion is evaluated based on:

- Improvement over single-modality models
- Robustness to missing or noisy modality data
- Consistency across different patient samples

Effective fusion improves the model's ability to capture both structural and functional information.

5.3 Model Performance and Robustness

Model robustness is evaluated based on:

- **Generalization:** Performance across different datasets
- **Noise tolerance:** Handling low-quality or noisy images
- **Modality variation:** Differences in X-ray, CT, MRI, and SPECT data

Challenges include data imbalance, variability in image quality, and alignment issues between modalities. Techniques such as data augmentation, normalization, and transfer learning help improve robustness.

5.4 Computational and Clinical Considerations

In practical deployment, the system must balance performance with efficiency:

- **Computation Time:** Faster inference is required for clinical usability
- **Model Complexity:** Deep models should be optimized for real-time or near real-time use
- **Interpretability:** Models should provide explainable outputs (e.g., heatmaps) to support clinical decisions

VI. DATASETS AND EVALUATION

6.1 Datasets

A multimodal bone cancer detection system typically utilizes datasets from different medical imaging modalities:

• **X-ray Datasets**: Used for initial screening of bone abnormalities; commonly include labeled images of normal and cancerous bones.

• **CT Scan Datasets**: Provide high-resolution 3D structural information for detecting cortical damage and bone lesions.

• **MRI Datasets:** Capture soft tissue and bone marrow involvement, useful for identifying tumor spread.

• **SPECT Datasets:** Functional imaging datasets that highlight metabolic activity and are effective for early metastasis detection.

• **Multimodal Datasets:** Combined datasets containing aligned X-ray, CT, MRI, and SPECT images are limited but highly valuable for training fusion models.

Due to limited availability of large annotated datasets, transfer learning and data augmentation are often used to improve model performance.

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6.2 Evaluation Metrics

- **Accuracy**: Overall correctness of classification
- **Precision**: Correctness of positive (cancer) predictions
- **Recall** (Sensitivity): Ability to detect actual cancer cases
- **Specificity**: Ability to correctly identify non-cancer cases
- **F1-score**: Balance between precision and recall
- **AUC** (Area Under Curve): Measures model's discrimination ability
- Confusion Matrix: Provides class-wise performance analysis

System-Level Metrics:

- Inference Time: Time taken to process one patient/sample
- Computational Efficiency: CPU/GPU usage during model execution
- Robustness: Performance under noisy or incomplete modality data
- Generalization: Model performance across different datasets

Unlike real-time systems, medical diagnosis systems focus more on accuracy, reliability, and consistency rather than FPS or latency.

Ref	Year	Modality	Model Used	Fusion Type	Performance	Key Strength	Limitation
[1]	2023	X-ray	CNN	None	High	Fast and simple detection	Limited feature representation
[2]	2024	MRI	Deep Learning	None	High	Good soft tissue analysis	Single modality limitation
[3]	2024	CT	EfficientNetB0	None	High	Efficient feature extraction	Lacks multimodal integration
[4]	2025	MRI + CT	CNN Fusion	Feature-level	Very High	Improved accuracy using fusion	High computational cost
[5]	2025	MRI + CT	Attention-based Model	Adaptive Fusion	Very High	Better feature weighting	Complex model training
[6]	2025	Multimodal	Image Fusion Model	Hybrid Fusion	High	Accurate tumor boundary detection	Data alignment challenges
[7]	2016	General	ResNet	—	High	Deep feature extraction	Overfitting risk
[8]	2017	General	DenseNet	—	High	Feature reuse and efficiency	Computationally heavy
[9]	2019	General	EfficientNet	—	High	Scalable and efficient model	Requires hyperparameter tuning

Comparative Analysis of Existing Deep Learning Approaches for Bone Cancer Detection

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6.3 Detailed Comparative Study

A comprehensive comparison of existing research works in bone cancer and tumor detection using deep learning techniques is presented in Table 1. The comparison considers multiple factors such as imaging modality, model architecture, fusion strategy, performance, strengths, and limitations.

6.4 Comparative Analysis Discussion

The comparative study highlights that single-modality approaches, such as X-ray, CT, and MRI-based models, achieve good performance in controlled scenarios but are limited in capturing comprehensive diagnostic information. These models fail to integrate complementary anatomical and functional features, which are crucial for accurate cancer detection.

In contrast, multimodal approaches significantly improve diagnostic performance by combining multiple imaging modalities. Feature-level and attention-based fusion techniques enhance the model's ability to capture diverse patterns, leading to improved classification accuracy and robustness [4], [5]. These approaches leverage the strengths of different modalities, such as structural information from CT and soft tissue details from MRI.

However, multimodal systems introduce several challenges, including increased computational complexity, difficulty in aligning heterogeneous data, and the requirement for large annotated datasets. Advanced deep learning architectures such as ResNet [9], DenseNet [10], and EfficientNet [11] further improve feature extraction capabilities but require careful optimization to avoid overfitting.

Overall, multimodal deep learning combined with adaptive fusion strategies represents the most promising approach for bone cancer detection. Future research should focus on developing efficient, interpretable, and scalable models for real-world clinical applications.

6.5 Research Gap

Despite significant advancements, several research gaps still exist in this domain. Most existing studies rely on limited datasets and focus on specific imaging modalities. There is a lack of standardized multimodal datasets and efficient fusion techniques that can be applied in real-world clinical environments.

Additionally, many deep learning models lack interpretability, which limits their adoption in healthcare. Therefore, future work should focus on integrating explainable AI techniques, optimizing computational efficiency, and combining imaging data with clinical information to enhance diagnostic performance.

VII. RESULTS AND DISCUSSION

7.1 System-Level Behavior and Practical Utility

In a multimodal bone cancer detection system, the output should be accurate, interpretable, and clinically useful. For example:
• If structural abnormalities are detected in CT and confirmed by MRI → high confidence malignant prediction.
• If SPECT shows abnormal metabolic activity but CT is unclear → early-stage metastasis indication.
• If all modalities indicate normal patterns → benign classification.
A key advantage of multimodal fusion is **improved decision reliability**, where the system combines evidence from multiple sources instead of relying on a single modality.

7.2 Robustness Considerations

Medical imaging systems must handle real-world variability such as:
• Differences in image quality across modalities
• Noise and artifacts in scans
• Misalignment between multimodal images
• Limited and imbalanced datasets
Robustness can be improved using:
• Data augmentation and normalization
• Transfer learning for small datasets

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• Proper image registration (alignment) techniques
• Fusion strategies that handle missing modalities

7.3 Computational Feasibility

Multimodal systems are computationally intensive due to multiple deep learning models. Practical solutions include:
• Using lightweight CNN architectures for faster inference
• Processing each modality in parallel
• Optimizing fusion techniques to reduce overhead
• Utilizing GPU acceleration for faster computation

7.4 Clinical Utility and Interpretability

For real-world adoption, the system should:
• Provide confidence scores with predictions
• Generate visual explanations (e.g., heat maps)
• Assist doctors rather than replace decision-making
• Maintain consistency and reliability across cases

VIII. ETHICAL, PRIVACY, AND FAIRNESS CONSIDERATIONS

Medical AI systems must follow ethical guidelines:
• **Data Privacy:** Patient data should be securely stored and anonymized
• **Transparency:** The model's decisions should be explainable
• **Fairness:** Models should perform consistently across different patient groups
• **Clinical Responsibility:** AI should assist doctors, not replace them
• **Regulation Compliance:** Follow healthcare standards and guidelines

IX. CONCLUSION AND FUTURE DIRECTIONS

This work presents a multimodal deep learning approach for bone cancer and bone metastasis detection by integrating X-ray, CT, MRI, and SPECT imaging. The integration of multiple imaging modalities significantly enhances diagnostic accuracy, robustness, and clinical reliability compared to traditional single-modality approaches.

Future research directions include:
• Development of large-scale multimodal datasets
• Improved fusion techniques with better alignment
• Explainable AI models for clinical trust
• Integration of clinical and patient data with imaging
• Real-time and cost-effective deployment in healthcare systems

These advancements demonstrate the potential of multimodal deep learning systems to support real-time clinical decision-making and improve patient outcomes.

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