A Survey of AI-Assisted Tumor Diagnosis and Precision Oncology in Medical Imaging Analysis

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Abstract

The integration of artificial intelligence (AI) and machine learning (ML) into healthcare has significantly transformed tumor diagnosis and treatment by enhancing diagnostic accuracy and optimizing clinical workflows. This survey paper provides a comprehensive overview of the current state of AI and ML applications in healthcare, focusing on their transformative impact on tumor diagnosis, AI-assisted treatment plans, and precision oncology. Deep learning techniques, particularly convolutional neural networks (CNNs), have been pivotal in automating feature extraction, improving diagnostic accuracy in medical imaging, and facilitating precise tumor detection and classification. AI-driven computer-aided diagnosis (CAD) systems have become indispensable in early cancer detection, such as breast and lung cancers, by enhancing radiologists' performance and improving patient outcomes. Despite these advancements, challenges such as algorithmic fairness and biases persist, potentially leading to inequitable healthcare delivery. Addressing these challenges is crucial for ensuring that AI-driven healthcare solutions are equitable and beneficial for all patients. This survey aims to provide a comprehensive framework for understanding and implementing AI and ML technologies in medical imaging analysis, with a focus on advancing precision oncology to tailor personalized treatment strategies. The paper also explores the integration of genomic and imaging data, the development of hybrid and ensemble models, and the importance of explainability and interpretability in AI models for clinical decision-making. By addressing these challenges and fostering interdisciplinary collaboration, the survey aims to contribute to the ongoing discourse on precision oncology and the integration of AI technologies in healthcare, ultimately improving patient outcomes and advancing personalized treatment strategies.

1 Introduction

1.1 Significance of AI and Machine Learning in Healthcare

The integration of artificial intelligence (AI) and machine learning (ML) into healthcare has significantly transformed tumor diagnosis and treatment, enhancing diagnostic accuracy and optimizing clinical workflows. Deep learning techniques, especially convolutional neural networks (CNNs), have automated feature extraction, allowing direct utilization of image data for tumor detection and classification without prior segmentation. This advancement improves cancer diagnosis and treatment planning by integrating weakly supervised learning techniques, which leverage clinical reports for tumor localization, thus reducing reliance on expert annotations while maintaining high detection accuracy. Such methodologies streamline diagnostics and support personalized treatment strategies, ultimately leading to better patient outcomes in cancer care [1, 2, 3, 4].

AI's role is particularly critical in breast cancer detection, addressing its rising incidence as a leading cause of death among women worldwide. Early detection is vital for improving survival rates, and AI-driven computer-aided diagnosis (CAD) systems are increasingly adopted for their reliability and

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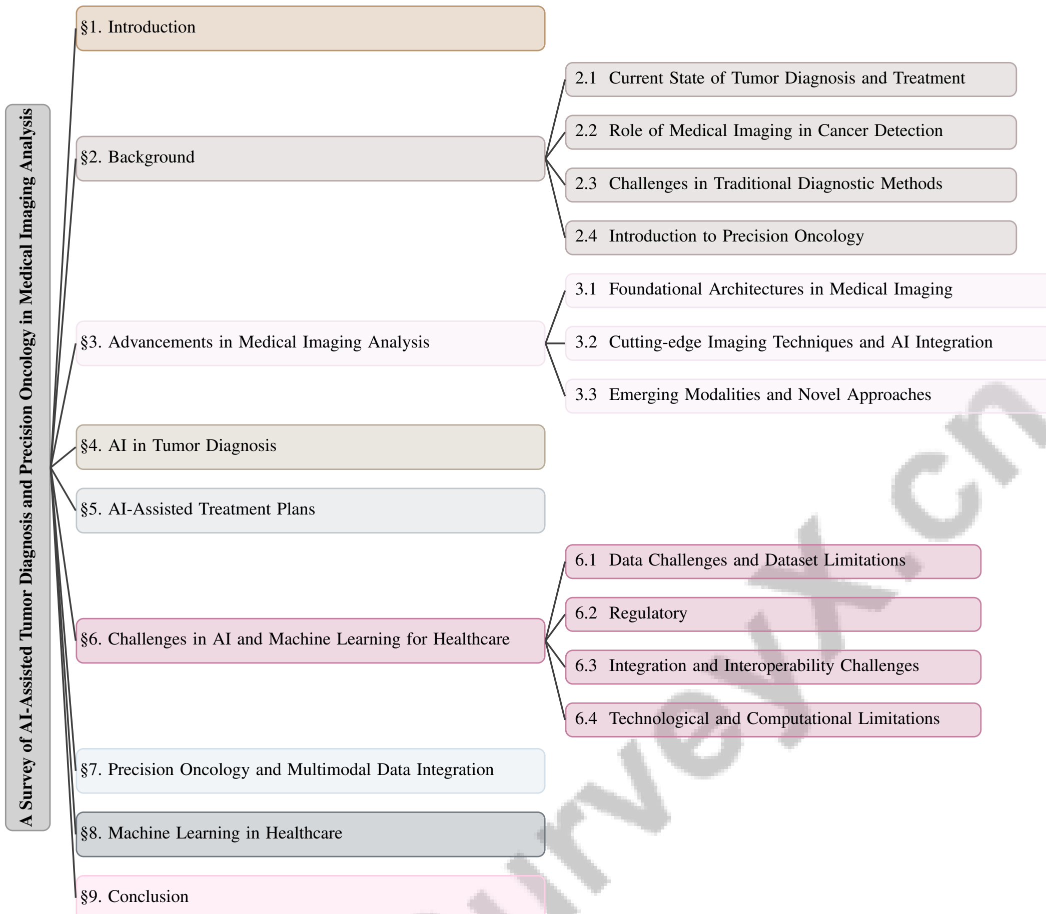

Figure 1: chapter structure

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accuracy. The application of CNNs in mammogram mass classification enhances early detection and improves radiologists' diagnostic precision [5].

The impact of AI extends to other cancers, notably lung cancer, emphasizing the need for early detection to improve survival rates and reduce the economic burden associated with late diagnoses. AI systems also support early diagnosis in prostate cancer, the second most diagnosed malignancy in men, which is essential for effective treatment [6]. Additionally, AI aids in the early identification of malignant pulmonary nodules, improving lung cancer prognosis by assisting radiologists in overcoming the complexities of manual assessments.

In skin cancer, the most frequently diagnosed cancer in the U.S., traditional detection methods often rely on dermoscopy images while neglecting critical clinical information. The integration of Large Language Models (LLMs) further enhances AI's role in healthcare, improving clinical decision-making tasks such as image captioning and report generation [7]. The emergence of explainable AI (XAI) techniques aims to bolster transparency and interpretability in ML models, fostering clinical trust and adoption.

Despite significant advancements, algorithmic fairness remains a critical challenge in healthcare. Research shows that biases in AI systems—arising from data acquisition, genetic variation, and intra-observer labeling variability—can lead to disparities in diagnosis, treatment, and billing practices across demographic groups. These inequities threaten to perpetuate existing healthcare disparities, particularly affecting underrepresented communities. Addressing these fairness concerns through strategies like disentanglement, federated learning, and model explainability is essential for ensuring equitable AI applications in healthcare [8, 9, 10]. The ongoing evolution of AI and ML technologies promises to further revolutionize medical imaging analysis, enhancing tumor diagnosis and treatment strategies. This survey aims to provide a comprehensive framework for understanding and imple-

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menting these transformative technologies to improve patient outcomes and advance personalized treatment strategies.

1.2 Motivation and Relevance of the Survey

This survey is motivated by the urgent need to leverage advanced technologies, specifically AI and ML, to enhance early cancer diagnosis and treatment, thereby improving patient outcomes and reducing the economic burden of cancer care. This is particularly critical for breast cancer, a leading cause of mortality among women globally. The survey addresses existing methodological gaps and evaluates various ML algorithms' performance in predicting breast cancer, facilitating model comparisons and advancing research in this domain [11].

The survey also tackles challenges related to lung cancer detection, focusing on the accuracy and interpretation of traditional CT scan methods, which often lead to late-stage diagnoses [12]. By exploring ML's deployment in healthcare, this survey identifies systemic challenges and ethical implications, emphasizing stakeholder engagement in technology integration [13].

Additionally, the survey highlights the importance of early detection in high-risk groups for cancers such as melanoma and pancreatic cancer, where effective early detection is crucial for better prognosis and treatment outcomes. Current diagnostic methods often rely on invasive and time-consuming procedures, underscoring the need for AI-driven enhancements in clinical workflows [14].

In the realm of precision oncology, the survey emphasizes the integration of genomic studies with AI to optimize treatment strategies and address challenges in cancer therapy [15]. It also discusses adapting generalist LLMs for specialized medical applications, which is vital for advancing personalized treatment strategies [16].

Moreover, the survey aims to bridge the gap between research advancements and the practical implementation of deep learning-based CAD tools in clinical workflows. It evaluates AI systems for prostate cancer detection and grading, comparing them with existing commercial alternatives to optimize workflow and improve diagnostic accuracy [17]. By focusing on applications in radiology, genetics, electronic health records, and neuroimaging, the survey provides a comprehensive overview of ML's role in advancing healthcare practices [18].

This survey seeks to enrich the dialogue surrounding precision oncology and AI integration in healthcare by examining the latest advancements in natural language processing, LLMs, and multimodal AI applications. By leveraging these technologies, the survey aims to facilitate the extraction of critical concepts from biomedical literature, enhance patient-specific data analysis, and ultimately improve patient outcomes through the development of personalized treatment strategies tailored to individual cancer profiles [19, 20, 21, 7, 22].

1.3 Structure of the Survey

This survey is structured to comprehensively explore the integration of AI and ML in tumor diagnosis and precision oncology, particularly through medical imaging analysis. The paper begins with an **Introduction** section, highlighting the significance of AI and ML in healthcare, discussing the motivation and relevance of the survey, and outlining its structure. The **Background** section follows, delving into the current state of tumor diagnosis and treatment, the role of medical imaging in cancer detection, and challenges faced by traditional diagnostic methods, while introducing the concept of precision oncology and its relevance to personalized medicine.

The third section, **Advancements in Medical Imaging Analysis**, examines medical imaging's role in cancer detection and diagnosis, exploring foundational architectures, cutting-edge imaging techniques, and emerging modalities that integrate AI and ML. The subsequent section, **AI in Tumor Diagnosis**, focuses on AI applications, particularly deep learning models, in detecting various tumor types and discusses the importance of explainability and interpretability in AI models for clinical use.

In **AI-Assisted Treatment Plans**, the survey explores how AI guides treatment plans in precision oncology and examines AI-driven clinical decision support systems. The section on **Challenges in AI and Machine Learning for Healthcare** identifies and discusses the challenges of integrating AI and ML in healthcare, including data challenges, regulatory and ethical concerns, and technological limitations.

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The survey then shifts focus to **Precision Oncology and Multimodal Data Integration**, exploring the integration of various data modalities to advance precision oncology. This is followed by an overview of **Machine Learning in Healthcare**, highlighting federated learning, data privacy, and methods for enhancing data robustness. Finally, the survey concludes with a **Conclusion** section, summarizing key findings and discussing the potential impact on personalized treatment strategies and future research directions.The following sections are organized as shown in Figure 1.

2 Background

2.1 Current State of Tumor Diagnosis and Treatment

The integration of traditional and technological methodologies defines the current landscape of tumor diagnosis and treatment. Histopathological analysis remains vital for identifying malignancies such as lung and colorectal cancers, which is crucial for effective treatment strategies. Recent advancements in machine learning and deep learning have significantly enhanced the speed and accuracy of cancer detection. For instance, a hybrid ensemble feature extraction model achieved 99.05

Breast cancer, the most prevalent cancer among U.S. women, results in approximately 42,000 deaths annually, underscoring the importance of early detection via screening mammography. Despite its significance, mammography often yields high false-positive rates, leading to unnecessary recalls and biopsies. Deep learning-based computer-aided diagnosis systems show promise in improving detection accuracy, facilitating precise diagnosis and treatment planning [23].

In prostate cancer diagnosis, conventional methods like Digital Rectal Exam (DRE), Prostate-Specific Antigen (PSA) testing, and transrectal ultrasound-guided biopsy suffer from sampling bias and difficulties in accurate prostate delineation during radiotherapy. AI-assisted frameworks are increasingly adopted to enhance detection and grading accuracy, reflecting the demand for more precise pathology services [24].

Oral cancer diagnosis traditionally relies on invasive histological examinations, but there is a shift towards non-invasive methods like brush biopsies and cytological assessments to streamline diagnostics and minimize patient discomfort. Additionally, natural language processing (NLP) in cancer pathology reports has focused on detecting cancer cases, often overlooking precancerous conditions, representing an area for further exploration [25].

The exploration of advanced technologies such as hybrid quantum machine learning models for histopathological cancer detection promises enhanced accuracy through quantum transfer learning [26]. These advancements reflect a broader trend toward adopting machine learning and AI technologies in medical imaging, poised to revolutionize tumor diagnosis and treatment strategies, ultimately improving patient outcomes.

2.2 Role of Medical Imaging in Cancer Detection

Medical imaging plays a pivotal role in cancer detection, offering critical insights that aid in accurate diagnosis and effective treatment planning. Various imaging modalities, each with unique advantages and challenges, are employed. In breast cancer detection, mammograms, ultrasounds, magnetic resonance imaging (MRI), and histopathological images are extensively used, significantly improving early detection rates and reducing mortality [27]. The BreakHis dataset, featuring histopathological images from 82 patients, exemplifies imaging's role in analyzing breast cancer lesions at varying magnification levels, enhancing diagnostic precision [28]. The Wisconsin Diagnostic Breast Cancer (WDBC) dataset, containing features from digitized fine needle aspirates, further underscores imaging's importance in identifying malignant breast tumors [29].

Digital mammograms (DM) and digital breast tomosynthesis (DBT) are primary techniques in clinical settings. However, existing computer-aided diagnosis (CAD) tools often focus on a single modality, leading to inefficiencies. Integrating multiple imaging modalities is crucial for comprehensive breast cancer diagnosis, leveraging each technique's strengths for a holistic tumor assessment [30]. The dataset from the UK National Health Service Breast Screening Programme and a U.S. academic medical center highlights these imaging modalities' clinical relevance across diverse populations [31].

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In prostate cancer detection, MRI scans are the most effective non-invasive diagnostic tool. A dataset comprising 23,833 prostate biopsy slides from Northwestern Memorial Hospital illustrates advanced imaging techniques' application in enhancing diagnostic accuracy and treatment outcomes [17]. The anticipated rise in MRI demand by 2040 underscores its critical role in prostate cancer diagnosis [24].

Recent advancements in weakly semi-supervised learning and AI-assisted algorithms further emphasize medical imaging's importance in early cancer detection. These methods enhance detection accuracy by utilizing clinical reports for weak tumor annotations, significantly reducing the need for expert-level labeling by over 70

2.3 Challenges in Traditional Diagnostic Methods

Traditional diagnostic methods in oncology face several challenges that compromise accuracy and reliability. A significant issue is the subjective nature of existing scoring systems, heavily reliant on human pathologists' interpretations, leading to variability in diagnostic accuracy and potential misdiagnoses, particularly among less experienced dermatologists. The manual review of pathology reports, especially in colorectal cancer, is time-consuming and costly, often resulting in ineffective cancer status classification [25].

In breast cancer diagnostics, reliance on RNA extraction from fresh tissue poses a significant obstacle, as this practice is often unfeasible in many clinical settings. This limitation, combined with inadequate pathology workflows, hampers accurate tumor characteristics assessment and subsequent treatment planning [23]. Similarly, prostate cancer diagnosis encounters challenges with MRI sequence registration, leading to misalignment of image features and difficulties in accurately detecting and characterizing lesions [24].

Lung cancer detection is frequently hindered by high false positive rates due to methods heavily dependent on hand-crafted features, which may not sufficiently differentiate between cancerous and healthy tissues [32]. Additionally, noise in histological images can degrade classification performance, complicating accurate diagnosis [26].

Moreover, the subjective nature of existing scoring systems and the labor-intensive process of comparing results present significant obstacles to effective oncological case classification [33]. This subjectivity is compounded by hidden stratifications within clinical data, leading to clinically meaningful errors and misclassifications [34].

The reliance on hand-crafted features in imaging-based detection methods poses challenges, as these features may inadequately differentiate between cancerous and healthy tissues, impacting diagnostic accuracy [32]. Furthermore, the dependency on RNA extraction from fresh tissue presents a critical barrier to adopting pathology workflows capable of accurately assessing tumor status [23].

Lastly, the scarcity of large, annotated datasets for training deep learning models, along with class imbalances and biases, presents significant barriers to achieving diagnostic accuracy comparable to human experts. This challenge is exacerbated by the need for specialized medical professionals to annotate data, a process demanding significant time investment and incurring high costs, particularly in precision oncology, where accurate identification of cancer types, mutations, treatments, and outcomes is critical for effective decision-making and the application of advanced natural language processing techniques [20, 22]. These limitations underscore the necessity for advanced AI-driven solutions that can address traditional diagnostic methods' inherent challenges and enhance cancer diagnostics' precision and reliability.

2.4 Introduction to Precision Oncology

Precision oncology represents a transformative approach in cancer treatment, emphasizing healthcare customization based on individual genetic and molecular tumor profiles. This paradigm shift arises from recognizing the genetic heterogeneity characterizing cancer, necessitating personalized treatment strategies to enhance patient outcomes [11]. By leveraging advances in genomic data, precision oncology aims to tailor treatments to each patient's unique molecular characteristics, improving therapeutic efficacy and minimizing adverse effects.

The integration of advanced technologies such as artificial intelligence (AI) and machine learning (ML) into precision oncology has further propelled this field. These technologies facilitate the

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analysis of complex datasets, enabling the identification of patterns and relationships that may not be immediately apparent to human clinicians. For instance, the automation of lung cancer detection, as explored by [35], aligns with precision oncology principles by enhancing diagnosis accuracy and speed through AI-driven methodologies.

Central to precision oncology is genomic data's use to guide treatment decisions, allowing for therapies tailored to individual tumors' genetic makeup. This approach effectively addresses cancer's inherent heterogeneity, arising from genetic variations among patients and the complex interplay of factors such as tumor location, cell of origin, and individual genomic alterations. By integrating multi-omics technologies and advanced analytical methods, this strategy aims to enhance understanding of both inter- and intra-tumor diversity, enabling oncologists to tailor treatment regimens more precisely to each patient's cancer characteristics [36, 37]. By leveraging genomic data, precision oncology seeks to identify the most effective treatment strategies for each patient, minimizing adverse effects and improving outcomes.

A key component of precision oncology is multimodal data integration, providing a comprehensive view of the patient's molecular profile. This integration is exemplified by innovative frameworks combining genomic, imaging, and clinical data to enhance cancer diagnosis and treatment accuracy and efficacy. For instance, in lung cancer detection, precision oncology principles are applied through diagnostic processes automation, leveraging AI and ML to improve early detection and prognostic accuracy [35].

Despite its potential, precision oncology faces challenges, particularly regarding data heterogeneity and the risk of misinterpreting model performance due to algorithmic bias. Effectively addressing these challenges is essential for realizing precision oncology's potential to deliver more effective and personalized cancer treatment strategies. This involves leveraging advancements in genomic and transcriptomic analyses to understand tumors' complex genetic and non-genetic heterogeneity, identifying relevant biomarkers correlating with treatment responses, and integrating comprehensive genomic data into clinical practice. By overcoming logistical, regulatory, financial, and ethical barriers, precision oncology can enhance cancer diagnosis, treatment, and monitoring, ultimately leading to targeted therapies addressing individual tumors' unique characteristics [37]. The ongoing integration of genomic data with imaging and other clinical data is critical for overcoming these challenges and advancing the field. As precision oncology evolves, it holds the potential to significantly improve patient outcomes by tailoring therapies to individual molecular profiles, thereby enhancing cancer treatments' efficacy and minimizing adverse effects.

3 Advancements in Medical Imaging Analysis

Recent advancements in medical imaging analysis have been significantly driven by the integration of artificial intelligence (AI) and machine learning (ML) technologies. These innovations have improved cancer detection and diagnosis accuracy while introducing novel methodologies that utilize complex data structures and advanced computational techniques. Understanding the foundational architectures in medical imaging, particularly those enhanced by deep learning and explainable AI, is essential for grasping how these developments facilitate advanced imaging techniques and AI applications in oncology, ultimately enhancing diagnostic accuracy and treatment personalization [38, 39, 22].

As illustrated in Figure 2, the hierarchical structure of advancements in medical imaging analysis highlights the interplay between foundational architectures, cutting-edge techniques, and emerging modalities. Foundational architectures leverage AI and ML, including convolutional neural networks (CNNs) and Vision Transformers, to enhance feature extraction and image analysis. Furthermore, cutting-edge techniques integrate deep learning algorithms and advanced AI models, such as CLIP and CAFNet, to improve diagnostic precision. Finally, emerging modalities focus on innovative frameworks like UMEML and the integration of genomic technologies, which are pivotal for personalized cancer diagnostics and treatment strategies. This comprehensive overview underscores the transformative impact of these technologies on the field of medical imaging.

3.1 Foundational Architectures in Medical Imaging

The incorporation of AI and ML into medical imaging has transformed cancer detection and diagnosis through foundational architectures like Convolutional Neural Networks (CNNs). These architectures

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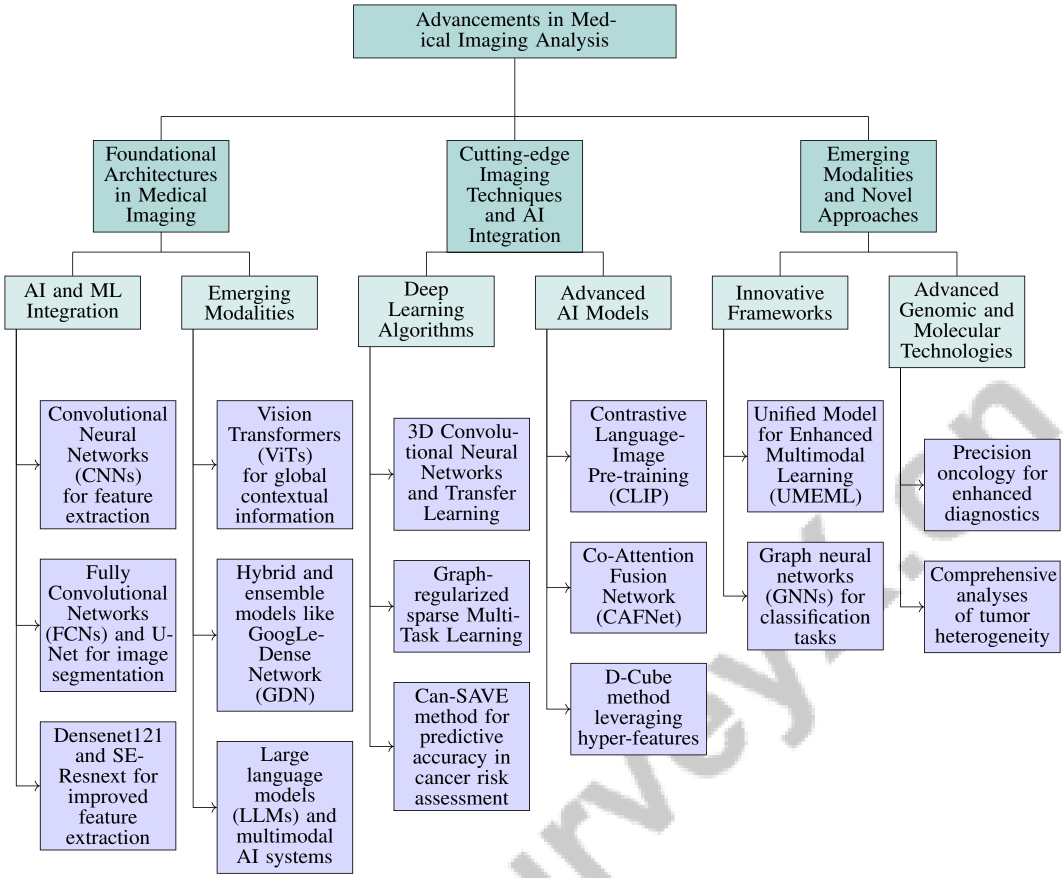

Figure 2: This figure illustrates the hierarchical structure of advancements in medical imaging analysis, highlighting foundational architectures, cutting-edge techniques, and emerging modalities. Foundational architectures leverage AI and ML, including CNNs and Vision Transformers, to enhance feature extraction and image analysis. Cutting-edge techniques integrate deep learning algorithms and advanced AI models, such as CLIP and CAFNet, to improve diagnostic precision. Emerging modalities focus on innovative frameworks like UMEML and the integration of genomic technologies for personalized cancer diagnostics and treatment strategies.

automate feature extraction, enabling direct analysis of image data without manual intervention, thus improving diagnostic accuracy and efficiency in tumor identification and classification [40]. In breast cancer detection, AI-driven computer-aided diagnosis (CAD) systems utilize CNNs to classify mammogram images as normal, benign, or malignant, thereby enhancing early detection rates and reducing mortality.

Advanced architectures such as Fully Convolutional Networks (FCNs) and U-Net play a crucial role in segmenting medical images, which is vital for identifying and localizing tumors within complex anatomical structures [40]. The development of sophisticated models like Densenet121 and SE-Resnext, which incorporate dense connections and squeeze-and-excitation blocks, further improves feature extraction and classification accuracy, advancing diagnostic capabilities.

Emerging modalities such as Vision Transformers (ViTs) are gaining traction in medical imaging analysis, utilizing self-attention mechanisms to capture global contextual information, thus offering powerful tools for analyzing complex medical images [25]. Hybrid and ensemble models, exemplified by the GoogLe-Dense Network (GDN), have shown significant improvements in diagnostic accuracy by combining predictions from multiple models, particularly in skin cancer diagnosis.

The integration of large language models (LLMs) and multimodal AI systems further enhances medical imaging analysis by combining genomic, imaging, and clinical data to improve diagnostic precision and treatment strategies. Notably, deformable registration methods have demonstrated

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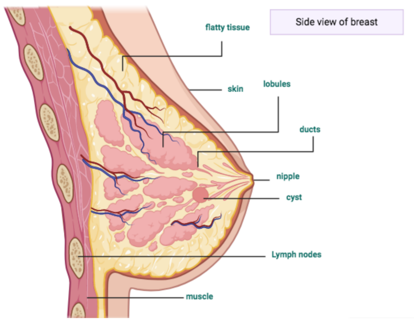
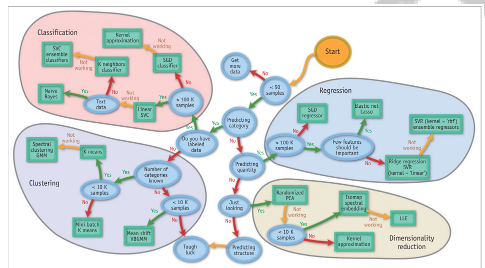
significant improvements in lesion overlap compared to rigid registration approaches, providing more accurate MRI sequence alignment, which is crucial for diagnosis and treatment planning [24].

The ongoing evolution of foundational architectures in medical imaging underscores the transformative potential of AI and ML technologies in healthcare. These innovations are set to enhance tumor diagnosis and treatment strategies by enabling more accurate, efficient, and personalized patient care. Deep learning techniques are increasingly integrated into various imaging modalities—such as MRI, CT, and ultrasound—to improve diagnostic accuracy, streamline workflows, and facilitate large dataset analysis. This evolution addresses existing clinical needs and overcomes challenges related to data heterogeneity and model interpretability, paving the way for the seamless incorporation of AI-driven solutions into routine clinical practice. As collaborations among clinicians, data scientists, and industry stakeholders expand, the potential for AI and ML to revolutionize cancer detection and treatment becomes increasingly tangible [41, 42, 27, 39, 28].



(a) Side View of Breast[43]



(b) Machine Learning Algorithms for Data Analysis[44]

Figure 3: Examples of Foundational Architectures in Medical Imaging

As illustrated in Figure 3, recent advancements in medical imaging analysis are exemplified by foundational architectures critical to the field. The first image depicts a detailed side view of a breast, showcasing intricate anatomical structures such as lobules and ducts, which are essential for understanding breast anatomy and aiding medical diagnostics. This visualization is vital for developing computer-aided systems that enhance breast cancer detection accuracy. The second image provides a structured flowchart of machine learning algorithms tailored for data analysis, categorizing them into classification, regression, and dimensionality reduction, thereby facilitating appropriate algorithm selection based on data characteristics. Together, these images emphasize the integration of anatomical knowledge and machine learning techniques, foundational in advancing medical imaging analysis and improving diagnostic accuracy and patient outcomes [43, 44].

3.2 Cutting-edge Imaging Techniques and AI Integration

Recent advancements in imaging techniques, alongside AI integration, have significantly bolstered diagnostic capabilities in oncology. The development of deep learning algorithms, particularly 3D Convolutional Neural Networks and Transfer Learning, has been pivotal, as evidenced by frameworks like graph-regularized sparse Multi-Task Learning, which enhances tumor detection accuracy [45]. Complementing these techniques, the Can-SAVE method utilizes electronic health record (EHR) data to derive meaningful features through survival analysis, improving predictive accuracy in cancer risk assessment [46].

Language-image models, such as Contrastive Language-Image Pre-training (CLIP) utilized in frameworks like Mammo-CLIP, enhance multi-view mammogram analysis, improving breast cancer diagnostics [47]. The Co-Attention Fusion Network (CAFNet) integrates features from brightfield and fluorescence imaging modalities, significantly enhancing oral cancer detection through improved imaging analysis [48].

In lung cancer detection, machine learning pipelines that co-learn from 3D CT images and clinical demographics have been developed to classify lung cancer nodules as benign or malignant, demonstrating the integration of imaging and demographic data for enhanced diagnostic precision [49]. The

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D-Cube method leverages hyper-features from diffusion models combined with contrastive learning, further enhancing classification accuracy in medical imaging [50].

A study by [51] showcased the integration of a commercially available AI algorithm (red dot®) alongside a panel of 11 clinicians with varying expertise levels, highlighting AI's potential in enhancing early lung cancer detection. Additionally, the evolutionary deep radiomic sequencer discovery framework proposed by [32] aims to evolve deep radiomic sequencers that are more efficient and capable of producing compact yet descriptive radiomic sequences.

Furthermore, the application of multiple instance learning (MIL) algorithms to characterize tumor and immune phenotypes from HE whole slide images (WSI) exemplifies AI's potential to enhance breast cancer outcome predictions [23]. These cutting-edge imaging techniques and AI integrations are paving the way for more precise and personalized cancer diagnostics, transforming oncology by enhancing diagnostic accuracy and efficiency. The continuous evolution of these technologies promises to further revolutionize medical imaging analysis, ultimately improving patient outcomes and advancing personalized treatment strategies.

As depicted in Figure 4, the hierarchical organization of cutting-edge imaging techniques and AI integration in oncology is illustrated, highlighting key deep learning algorithms, multi-modal frameworks, and AI-assisted diagnostic methods. The first part of the figure illustrates "Prompting Techniques in Natural Language Generation," presenting a flowchart categorizing prompts into "Manual" and "Automated" types, further divided into "Human-interpretable Text" and "Non-human-interpretable Embedding." This segmentation highlights nuanced approaches in AI-driven language processing, applicable to medical imaging for enhanced data interpretation and decision-making. The second part of the figure, "Area under the ROC curve," showcases a box plot graph evaluating various data categories' performance in diagnostic accuracy, represented by the area under the Receiver Operating Characteristic (ROC) curve. This graph emphasizes the efficacy of AI algorithms in distinguishing different diagnostic categories, thereby enhancing medical imaging analysis precision. Together, these examples illustrate the transformative potential of AI and advanced imaging techniques in revolutionizing medical diagnostics and patient care [52, 42].

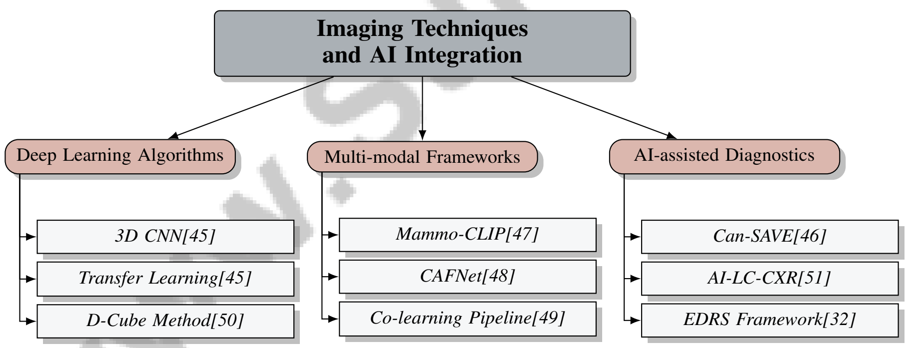

Figure 4: This figure illustrates the hierarchical organization of cutting-edge imaging techniques and AI integration in oncology, highlighting key deep learning algorithms, multi-modal frameworks, and AI-assisted diagnostic methods.

3.3 Emerging Modalities and Novel Approaches

The medical imaging landscape is continually evolving, with emerging modalities and novel approaches enhancing the capacity for accurate cancer diagnosis and treatment. One advancement is the Unified Model for Enhanced Multimodal Learning (UMEML) framework, which employs a hierarchical attention structure and a query-based cross-attention mechanism to address unimodal bias by aligning shared features across different modalities, thereby improving diagnostic accuracy [53].

Another innovative approach integrates cancer data modalities into a graph structure, as demonstrated by the application of graph neural networks (GNNs) in an unsupervised learning pipeline. This method generates lower-dimensional embeddings for classification tasks, showcasing GNNs' potential to enhance interpretability and efficiency in cancer diagnostics [54]. By leveraging the inherent

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relationships between diverse data modalities, this approach facilitates a comprehensive understanding of cancer pathology, ultimately aiding in more precise diagnosis and treatment planning.

These emerging modalities and novel approaches signify a shift towards more integrated and sophisticated diagnostic frameworks in medical imaging. The ongoing development and integration of advanced genomic and molecular technologies in precision oncology promise to enhance cancer diagnostics' accuracy and personalization. By leveraging comprehensive analyses of tumor heterogeneity, including genomic and transcriptomic profiling, these innovations aim to identify specific biomarkers and therapeutic targets, ultimately leading to improved patient outcomes and individualized treatment strategies that address each patient's unique molecular cancer characteristics [37, 19, 36, 15].

4 AI in Tumor Diagnosis

Category	Feature	Method
Deep Learning Models in Tumor Detection	Interpretability and Visualization	CAM[55]
	Architecture and Optimization	DBRNN[56], EDRS[32]
	Data Processing and Fusion	NRCA-FCFL[26]
	Text Analysis and Processing	TEL[25]
Hybrid and Ensemble Models	Multi-Scale and Attention Mechanisms	HCTM[57], MOL-ViT[6]
	Ensemble Voting Strategies	WAUCE[58]
	Semi-Supervised Learning Techniques	SKD[59]
Explainability and Interpretability in AI Models	Model Combination Methods	GDN[60]
	Advanced Feature Strategies	D-Cube[50]
	Data Integration Approaches	M-CLIP[47]
	Visual Representation Techniques	VOIHI[61]

Table 1: This table provides a comprehensive overview of various AI methodologies employed in tumor detection, focusing on deep learning models, hybrid and ensemble models, and explainability and interpretability techniques. It categorizes these methods based on their features and specific approaches, highlighting the diversity and sophistication of current AI applications in enhancing diagnostic precision and clinical outcomes in oncology.

AI's integration into tumor diagnosis is revolutionizing diagnostic accuracy and efficiency. This section delves into the methodologies, particularly deep learning models, that automate tumor detection. By employing sophisticated algorithms and extensive datasets, these models are redefining medical imaging and setting new benchmarks for precision in cancer diagnostics. Table 1 presents a detailed summary of AI methodologies in tumor detection, categorizing them into deep learning models, hybrid and ensemble models, and explainability and interpretability approaches, which are crucial for advancing diagnostic accuracy and clinical decision-making. The following subsection will explore deep learning models' mechanisms and advancements in tumor detection, highlighting their pivotal role in enhancing clinical outcomes.

4.1 Deep Learning Models in Tumor Detection

Method Name	Model Types	Diagnostic Applications	Challenges and Solutions
VOIHI[61]	Vgg19	Breast Cancer Classification	Transparency, Discrepancies
EDRS[32]	Deep Radiomic Sequencers	Lung Cancer Detection	Patient Privacy
NRCA-FCFL[26]	Vision Transformers	Osteosarcoma Detection	Noise Reduction
TEL[25]	Transformer Models	Colorectal Cancer	Data Extraction Challenge
CAM[55]	Cyclegans	Breast Cancer Detection	Transparency
DBRNN[56]	Bayesian Recurrent Networks	Somatic Variant Calling	Transparency, Data Privacy

Table 2: Overview of various deep learning methods and their applications in tumor detection, highlighting the specific model types, diagnostic applications, and associated challenges. The table provides insights into the use of different architectures, such as CNNs, Vision Transformers, and Bayesian Recurrent Networks, in the detection of various cancers, along with the challenges of transparency, patient privacy, and noise reduction.

Deep learning models, notably Convolutional Neural Networks (CNNs), have significantly transformed tumor detection by automating feature extraction, thus enhancing diagnostic precision and operational efficiency across various cancer types. CNN-based frameworks have outperformed human accuracy in breast cancer diagnostics through mammographic image classification [40]. Visualization techniques within CNN architectures, such as VGG19, improve the interpretability of histological image classification, offering insights into model decision-making [61].

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In lung cancer, deep learning models have notably increased diagnostic sensitivity and specificity. The evolutionary deep radiomic sequencer (EDRS) framework exemplifies the potential of deep learning in optimizing radiomic sequencers for lung cancer detection [32]. DenseNet models tackle dataset variability challenges, enhancing accuracy by evaluating hidden stratification effects [34].

Prostate cancer detection has also advanced with deep learning algorithms from the PI-CAI challenge, aimed at identifying clinically significant prostate cancer and improving detection and grading accuracy [24]. The NRCA-FCFL framework's precise classification of osteosarcoma histological images further underscores deep learning's superiority over traditional methods [26].

Transformer-based models in colorectal cancer diagnosis represent significant progress, utilizing these models to classify cancer statuses and extract lesion attributes from unstructured pathology report text [25]. This versatility highlights deep learning's ability to manage diverse data types and improve diagnostic workflows.

As illustrated in Figure 5, the hierarchical classification of deep learning models in tumor detection emphasizes the various cancer types, model types, and the challenges associated with their application. The figure highlights the roles of CNNs, DenseNet, and Transformers in detecting different cancers while addressing significant challenges such as transparency, data privacy, and noise reduction. Additionally, Table 2 presents a comprehensive summary of deep learning methods employed in tumor detection, detailing the model types, diagnostic applications, and challenges encountered in the implementation of these advanced techniques.

However, challenges such as decision-making transparency persist, potentially hindering clinician acceptance [55]. Addressing these issues is crucial to unlocking deep learning models' full potential in providing accurate, efficient, and personalized tumor diagnosis and treatment strategies. The ongoing evolution of AI and machine learning technologies promises to revolutionize medical imaging analysis, thereby enhancing tumor diagnosis and treatment strategies, ultimately improving patient outcomes [56].

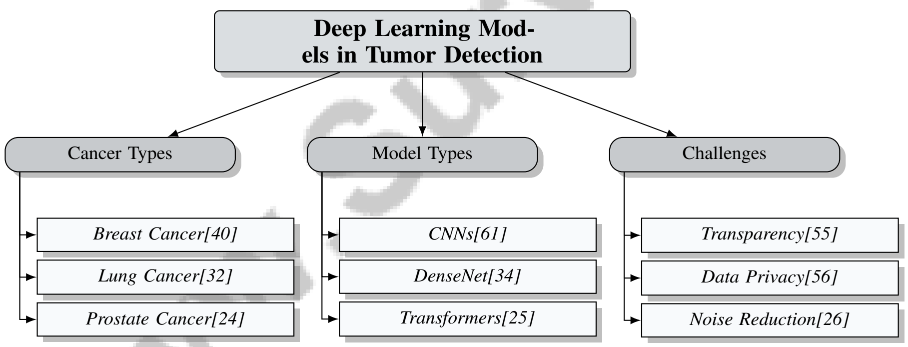

Figure 5: This figure shows the hierarchical classification of deep learning models in tumor detection, emphasizing cancer types, model types, and challenges. It highlights the application of CNNs, DenseNet, and Transformers in detecting various cancers, while addressing challenges such as transparency, data privacy, and noise reduction.

4.2 Hybrid and Ensemble Models

Hybrid and ensemble models are emerging as crucial strategies in medical imaging, enhancing diagnostic accuracy and overcoming single-model limitations. By integrating multiple models, these strategies leverage diverse algorithms' strengths, improving diagnostic systems' robustness and generalizability, especially in data-limited or imbalanced scenarios [62].

The WAUCE model, which integrates various Support Vector Machine (SVM) models, exemplifies this approach by enhancing classification performance through leveraging individual SVM strengths [58]. In breast cancer detection, a two-dimensional ARMA model combined with a k-means classifier effectively segments breast images, demonstrating hybrid models' potential in improving diagnostic precision.

In prostate cancer detection, integrating image transformers enhances classification performance through multi-scale predictions, showcasing hybrid models' ability to improve diagnostic accuracy

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[6]. Additionally, a U-shaped architecture using CNN encoders and a transformer bottleneck for cystoscopy image processing has redefined bladder cancer diagnostics, illustrating hybrid models' versatility and efficacy [57].

Semi-supervised frameworks, such as SelectiveKD, illustrate hybrid models' potential in cancer detection by using soft labels and selectively chosen unannotated data to improve model learning while minimizing noise from incorrect labels, thereby enhancing diagnostic accuracy [59].

The continuous development and integration of hybrid and ensemble models are poised to further revolutionize cancer diagnostics. These models effectively address traditional diagnostic methods' limitations and leverage multiple data sources and algorithms' strengths, promising significant improvements in diagnostic accuracy and patient outcomes. As precision oncology research progresses, large language models and multimodal AI systems' capabilities to enhance tumor diagnosis and treatment strategies are becoming increasingly evident. These models can process diverse data types from electronic health records, medical imaging, and genomic analyses simultaneously, improving cancer care's precision and effectiveness. Additionally, innovative natural language processing methods are being developed to extract critical concepts from biomedical literature, further supporting clinical decision-making and personalized treatment approaches [7, 22].

4.3 Explainability and Interpretability in AI Models

AI models' implementation in clinical settings, particularly for tumor diagnosis, necessitates a high degree of explainability and interpretability to ensure trust among clinicians and patients. The complexity of deep neural networks (DNNs) often results in a "black box" problem, where the model's decision-making process remains unclear, hindering acceptance and integration into clinical practice [61]. Addressing this challenge is crucial, as a lack of transparency can lead to difficulties in medical decision-making and potential clinical errors [63].

Recent advancements aim to enhance DNN-based clinical decision support systems' interpretability by generating high-quality visualizations that are both intuitively valid and semantically meaningful. Such visualizations enable clinicians to comprehend AI models' underlying decision processes, fostering trust and facilitating adoption in clinical settings [61].

Innovative approaches, such as Mammo-CLIP, which captures and integrates multi-view information, exemplify the potential to enhance AI models' interpretability in medical imaging [47]. By leveraging contrastive language-image pre-training, Mammo-CLIP improves multi-view information integration, enhancing diagnostic accuracy.

Challenges persist in achieving transparency and interpretability, particularly concerning complex data distributions and feature representation quality. The D-Cube method addresses these challenges by utilizing hyper-features from diffusion models, enhancing feature representation quality and medical diagnosis accuracy [50]. This approach illustrates advanced AI techniques' potential in capturing complex data distributions and improving medical imaging models' interpretability.

Developing transparent and clinically interpretable AI models is vital for their successful adoption in clinical settings. By addressing machine learning and deep learning models' opacity, researchers can mitigate challenges associated with the "black box" nature of these systems and enhance their clinical utility. This is particularly crucial in oncology, where AI models' interpretability is essential for effective medical decision-making and improved patient outcomes.

Furthermore, integrating genomic and imaging data in precision oncology underscores the importance of explainability and interpretability in AI models. Methods such as the GDN stacking network [60] and hyper-feature diffusion models [50] have shown significant potential in enhancing diagnostic accuracy and treatment strategies by capturing complex data distributions and improving feature representation quality. As precision oncology evolves, the need for transparent and interpretable AI models becomes increasingly critical to ensure reliable and effective cancer diagnostics and treatment planning.

5 AI-Assisted Treatment Plans

The integration of artificial intelligence (AI) into precision oncology is revolutionizing treatment plan development by enhancing the accuracy and efficiency of cancer treatment strategies. AI-driven

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clinical decision support systems (CDSS) enable healthcare professionals to make informed decisions, thereby improving patient outcomes. This section explores innovative frameworks that leverage AI to integrate genomic and imaging data, further refining treatment precision in oncology.

5.1 AI-Driven Clinical Decision Support Systems

AI-driven clinical decision support systems (CDSS) are transforming precision oncology by optimizing cancer treatment plans, improving patient outcomes, and reducing healthcare burdens. Karyotype-based AI models, such as KaryotypeAI, utilize genomic data to enhance diagnostic accuracy and tailor treatments to tumors' molecular profiles, thereby improving therapeutic efficacy and minimizing side effects [64]. AI systems have significantly improved diagnostic accuracy across various cancers, including breast cancer, where deep learning methods classify malignancy from HE whole slide images (WSIs) [23]. Additionally, a two-dimensional ARMA model combined with a k-means classifier enhances breast cancer diagnostic precision [58].

As illustrated in Figure 6, the categorization of AI-driven clinical decision support systems in oncology highlights key methods and tools in cancer detection, particularly in lung cancer diagnostics and various imaging modalities. Each category encompasses specific AI models and techniques that contribute to improved diagnostic accuracy and treatment planning. In lung cancer detection, AI systems that integrate imaging and clinical data have improved classification accuracy and reduced false positives [49]. Techniques like SinGAN-based data augmentation effectively mitigate annotation shifts, enhancing classification performance for malignant cases [65]. AI-driven CDSS extend to various imaging modalities, including ultrasound and MRI, where a 3D Convolutional Neural Network (CNN) achieves 99.17

The EpiSwitch platform showcases AI's transformative potential in cancer diagnostics and treatment by integrating genomic, imaging, and clinical data to provide personalized treatment recommendations, enhancing precision and efficacy [64]. As AI-driven CDSS evolve, they promise to revolutionize oncology practices, advancing precision oncology and improving patient outcomes.

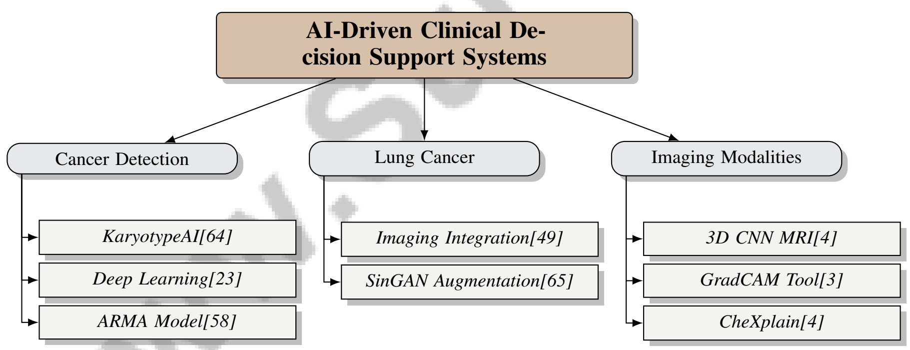

Figure 6: This figure illustrates the categorization of AI-driven clinical decision support systems in oncology, highlighting key methods and tools in cancer detection, lung cancer diagnostics, and imaging modalities. Each category includes specific AI models and techniques that contribute to improved diagnostic accuracy and treatment planning.

5.2 Integration of Genomic and Imaging Data

Integrating genomic and imaging data is pivotal in precision oncology, enabling therapies tailored to tumors' molecular and phenotypic characteristics. This approach harnesses diverse data modalities to enhance tumor biology understanding and therapeutic decision-making [37]. A significant advancement is the development of a knowledge graph that integrates genetic data, medical records, and established medical knowledge, translating complex genomic findings into clinical practice and addressing challenges like drug resistance and therapy personalization [66].

Incorporating domain knowledge on somatic mutations with statistical feature selection enhances cancer type prediction accuracy, underscoring genomic data's role in treatment strategies [67]. An ontology-driven treatment article retrieval system that includes disease, gene, and drug ontologies improves the relevance of retrieved articles for specific patient profiles, supporting informed therapeutic

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decisions [21]. Utilizing heterogeneous data types within a multimodal learning framework enhances drug response predictions in patient-derived xenografts (PDXs), improving classification performance and providing insights into cancer subtypes. This integration highlights the importance of combining genomic data, advanced molecular diagnostics, and imaging techniques to refine treatment strategies and advance precision oncology. By synthesizing these modalities, we can better understand tumor heterogeneity, enhance clinical decision-making, and foster targeted therapies tailored to individual patient needs [68, 25, 22, 69].

The ongoing development of methodologies integrating genomic, imaging, and clinical data is set to significantly enhance precision oncology. These approaches provide a multifaceted perspective on tumor heterogeneity, deepening our understanding of cancer biology and facilitating informed therapeutic decisions. This evolution is essential for identifying multimodal prognostic features and discovering novel biomarkers, leading to improved patient management and tailored treatment strategies. However, challenges such as data sparsity and the need for advanced computational methods persist in effectively harnessing this wealth of information [68, 37, 69]. As these techniques advance, they are expected to overcome traditional treatment limitations, enhance patient outcomes, and propel personalized cancer care forward.

6 Challenges in AI and Machine Learning for Healthcare

6.1 Data Challenges and Dataset Limitations

Benchmark	Size	Domain	Task Format	Metric
HSB[34]	112,120	Medical Imaging	Classification	ROC AUC
NLP-PO[22]	250	Precision Oncology	Concept Extraction	F1
MM-DST[70]	12	Oncology	Treatment Decision Making	Confidence Rating, Reliability Rating
ViT[71]	10,000	Dermatology	Image Classification	Accuracy, Recall
DIR[62]	1,920	Breast Cancer Detection	Image Classification	Accuracy, F1-score
PCam[72]	220,025	Histopathology	Image Classification	AUC, Precision
PCa-Error-Prop[73]	200	Prostate Cancer Detection	Lesion Detection	AUC, DSC
BCDDB[28]	7,909	Histopathology	Binary Classification	Accuracy, F1-Score

Table 3: This table presents a comprehensive overview of representative benchmarks utilized in the integration of AI and ML within healthcare, specifically focusing on tumor diagnosis and precision oncology. It details the size, domain, task format, and evaluation metrics of each benchmark, highlighting the diversity and scope of datasets used in this field.

AI and ML integration in healthcare, particularly for tumor diagnosis and precision oncology, faces significant challenges due to data heterogeneity and dataset limitations. Variability in imaging protocols and equipment complicates model generalization, necessitating robust models for consistent accuracy across platforms [33]. Fragmented data, privacy concerns, and the non-IID nature of medical data further impact model performance and integration. Limited dataset size and diversity often lead to overfitting, reducing generalizability across populations [74]. The scarcity of high-quality annotated datasets complicates model training, highlighting the need for innovative data augmentation and transfer learning [26]. Table 3 provides a detailed comparison of various benchmarks employed in healthcare AI applications, illustrating the challenges posed by dataset limitations and the need for robust model development. Existing benchmarks often overlook hidden stratification, resulting in misleading performance metrics [34]. The complexity of AI models obscures decision-making processes, hindering clinical acceptance [40]. Data scarcity, annotation difficulty, and low prevalence of early tumors limit AI's potential in cancer detection [75]. Ethical considerations are paramount, as AI models may reflect human biases, necessitating oversight to ensure equitable healthcare delivery [25]. Addressing these challenges is essential for enhancing AI efficacy in healthcare, emphasizing scalable frameworks to improve dataset diversity and accessibility [23].

6.2 Regulatory, Ethical, and Legal Concerns

AI and ML integration in healthcare, particularly in tumor diagnosis and precision oncology, raises regulatory, ethical, and legal challenges. The "black box" problem limits clinicians' interpretability of AI systems, undermining trust. Explainable AI systems like CheXplain address the need for transparency in medical applications [38, 63]. Interdisciplinary collaboration is essential to navigate

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AI complexities, establishing standards for ethical deployment [76]. Legal frameworks like GDPR impose stringent data privacy requirements, challenging AI integration. Privacy-preserving techniques like federated learning offer promising solutions [77]. Ethical considerations are critical, as biases in AI systems can exacerbate healthcare disparities. Strategies to ensure fair AI models are vital for equitable healthcare delivery [76]. Legal and ethical challenges regarding accountability, liability, and unintended consequences necessitate clear guidelines [76]. Successful AI integration requires a comprehensive approach addressing transparency, ethics, and collaboration, considering healthcare's complexity to maximize AI benefits [16, 78, 9, 79].

6.3 Integration and Interoperability Challenges

Integrating AI into healthcare infrastructure presents challenges, particularly achieving interoperability among disparate EHR systems. The diversity of EHR systems complicates AI model integration, impacting their ability to deliver personalized insights [9]. As illustrated in Figure 7, the figure highlights the key challenges in this integration process, emphasizing the necessity of interdisciplinary collaboration and the deployment challenges of AI technologies. Interdisciplinary collaboration is crucial for understanding machine learning contexts and devising effective AI deployment strategies [13]. Implementing AI in clinical settings requires algorithm design consideration and ethical implications related to patient care [80]. Balancing technological advancements with ethical responsibilities ensures AI systems enhance patient-physician relationships. Addressing integration challenges is critical for AI success in healthcare, leveraging diverse data sources to enhance precision medicine [41, 20, 22, 69].

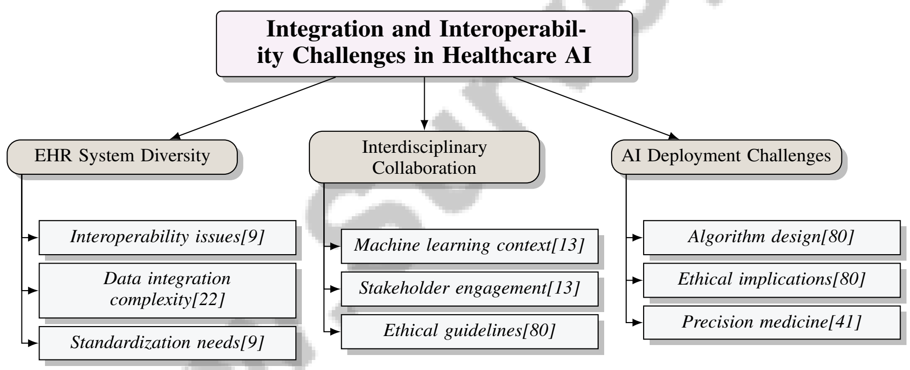

Figure 7: This figure illustrates the key challenges in integrating AI into healthcare, focusing on EHR system diversity, the necessity of interdisciplinary collaboration, and the deployment challenges of AI technologies.

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6.4 Technological and Computational Limitations

AI implementation in healthcare, particularly in tumor diagnosis and precision oncology, faces technological and computational challenges. The computational cost of training complex models like Bayesian neural networks hinders clinical adoption [56]. Scalability on quantum hardware is limited by current technological constraints [81]. Integrating CNNs into diagnostic pipelines, such as lung cancer detection, illustrates AI's potential but poses scalability challenges [43]. Robust frameworks are needed to manage diverse data sources, particularly from IoT devices [82]. Interpretability methods often provide only approximations, leading to misinterpretations [63]. Advanced AI approaches offer efficiency, improved accuracy, and local operation without compromising privacy [32]. Future research should focus on developing robust models that generalize across datasets and integrating AI into clinical workflows [43]. Addressing technological and computational limitations is essential for effective AI integration, focusing on scalable, efficient, and interpretable models to advance precision oncology [83, 38, 22, 79, 16].

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7 Precision Oncology and Multimodal Data Integration

7.1 Concept and Importance of Precision Oncology

Precision oncology represents a paradigm shift in cancer treatment, emphasizing personalized therapeutic strategies tailored to the genetic and molecular profiles of individual tumors. Recognizing tumor heterogeneity, this approach aims to enhance treatment efficacy and reduce side effects [15]. Central to this is the integration of multi-omics data, including genomic, transcriptomic, proteomic, and metabolomic analyses, providing a comprehensive understanding of tumor biology for informed treatment decisions [36].

Precision oncology benchmarks involve domain-specific concept extraction, distinct from traditional metrics, to identify biomarkers and therapeutic targets essential for personalized treatments [22]. Integrating diverse data modalities such as imaging, clinical records, and omics data is crucial for a holistic cancer understanding, enhancing diagnostic and therapeutic capabilities [68]. Biomarker identification facilitates therapy selection targeting specific molecular alterations, improving treatment efficacy [37]. Genomic profiling is vital for effective cancer therapies, particularly in addressing treatment resistance and tumor heterogeneity [15]. Despite genomic analyses' promise, challenges in standardization and clinical utility demonstration persist [84].

Integrating histopathology, radiology, genomics, and clinical data into predictive models is essential for advancing precision oncology [69]. The MT-BI-RADS multitask learning approach exemplifies enhanced treatment precision through BI-RADS descriptor prediction, tumor segmentation, and malignancy classification [85]. Explainability in machine learning systems is critical for safety assurance, necessitating complementing AI methods with clinical judgment to ensure effective AI-driven strategies [86]. Uncertainty quantification, particularly in high-stakes applications, is crucial, with confidence-aware neural networks underscoring the need to enhance decision-making and patient outcomes [87]. Precision oncology promises to revolutionize cancer treatment by offering personalized therapies that address tumor heterogeneity and treatment resistance complexities.

7.2 Techniques for Multimodal Data Integration

Multimodal data integration is vital for enhancing cancer diagnostics and treatment strategies in precision oncology. It synthesizes genomic, imaging, and clinical data to provide a comprehensive tumor biology understanding, informing personalized treatment decisions. Integration techniques include early, intermediate, late, and multi-level fusion strategies, each with distinct advantages and limitations [68].

Early fusion strategies combine raw data from various modalities at the initial analysis stage, leveraging complementary strengths for enhanced model interpretability. Intermediate fusion integrates features from different modalities later in the analysis, allowing for more abstract information synthesis. Late fusion merges outputs from independently trained models, offering flexibility and robustness through diverse predictive insights [68]. Multi-level fusion strategies utilize data's hierarchical nature, integrating information at various abstraction levels to improve model performance and clinical outcomes [88]. Exploring these strategies is crucial for advancing multimodal data integration, facilitating the development of accurate and reliable diagnostic and treatment models.

Future research should enhance model interpretability and robustness by integrating contextual information and exploring multimodal approaches incorporating genomic data. Developing effective transfer learning and domain adaptation techniques is essential for improving AI models' generalizability across diverse clinical settings [41]. Adapting generalist large language models (LLMs) to enhance multimodal capabilities is crucial for integrating various data modalities and advancing precision oncology [16]. Advanced deep learning techniques are necessary to ensure robust and trustworthy healthcare applications, addressing privacy concerns while enhancing AI-driven solutions' reliability in precision oncology [77]. By focusing on sophisticated multimodal integration techniques, researchers can unlock precision oncology's full potential, improving patient outcomes and advancing personalized cancer care.

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7.3 Advancements in Multimodal Data Integration

Recent advancements in multimodal data integration have significantly enhanced precision oncology, enabling comprehensive and accurate cancer diagnostics and treatment strategies. This integration leverages genomic, imaging, and clinical data for a holistic tumor biology understanding, proving effective in clinical applications such as diagnosis, prognosis, and treatment response prediction [68].

Sophisticated fusion strategies—early, intermediate, late, and multi-level fusion—facilitate seamless integration of diverse data modalities, extracting complementary insights that enhance model performance and clinical outcomes. Early fusion combines raw data at analysis's initial stages, while intermediate fusion integrates features later for a more abstract understanding. Late fusion merges outputs from independently trained models, providing flexibility and robustness, while multi-level fusion integrates information at various abstraction levels to improve performance [68].

Despite advancements, challenges remain in achieving seamless multimodal data integration and ensuring AI models' interpretability and robustness. Tumor heterogeneity necessitates synthesizing diverse data types—genomic, imaging, and clinical information—to enhance clinical decision-making. However, existing datasets are often sparse and underutilized, limiting modern machine learning techniques' effectiveness. While large language models and multimodal AI approaches show promise, further research is needed to tackle ongoing challenges in data integration and model reliability [68, 7, 22, 69]. Multimodal data complexity requires advanced deep learning techniques capable of handling diverse data types while addressing privacy and data security concerns. Integrating contextual information and exploring multimodal approaches, including genomic data, is vital for enhancing model interpretability and generalizability across varied clinical settings.

Future research should emphasize developing advanced techniques for effective transfer learning and domain adaptation, particularly in adapting generalist large language models (LLMs) for specialized medical applications. This focus is crucial for enhancing LLMs' multimodal capabilities, improving tasks like medical imaging analysis, clinical decision support, and precision oncology by integrating diverse data types and optimizing model performance. Addressing these challenges will facilitate more accurate diagnoses and treatment plans, streamline clinical workflows, and reduce diagnostic errors in healthcare [89, 16, 7, 22]. By advancing multimodal data integration techniques and addressing existing challenges, researchers can unlock precision oncology's full potential, improving patient outcomes and advancing personalized cancer care.

8 Machine Learning in Healthcare

8.1 Federated Learning and Data Privacy

Federated learning represents a pivotal advancement in addressing privacy concerns within healthcare, particularly in training AI models using sensitive medical data. This approach enables AI development across decentralized devices, ensuring that patient data remains localized, thus preserving confidentiality while allowing model training on diverse datasets [10]. The significance of federated learning in healthcare is highlighted by the sensitive nature of medical data and the stringent regulations governing its use. Federated learning offers a robust framework for overcoming challenges related to medical data heterogeneity and privacy, facilitating collaborative model training across institutions without compromising data security [90].

In precision oncology, federated learning is crucial for extracting key concepts from diverse biomedical datasets, advancing personalized treatment strategies. As demonstrated by [22], federated learning supports the training of NLP models on varied datasets while safeguarding patient information, aligning with the objectives of precision oncology.

8.2 Data Augmentation and Uncertainty Quantification

Data augmentation and uncertainty quantification are critical for enhancing AI model robustness and reliability in healthcare, particularly for tumor diagnosis and precision oncology. Advanced image processing algorithms diversify training datasets, improving AI models' generalization capabilities and addressing challenges of limited and imbalanced datasets, which can lead to overfitting [41, 22]. These techniques enhance diagnostic accuracy, streamline workflows, and improve patient outcomes while managing data heterogeneity and ensuring model interpretability for clinical integration.

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Uncertainty quantification is vital in high-stakes medical decision-making, offering insights into the reliability of AI-driven diagnostic and treatment recommendations by assessing model prediction confidence. This is crucial in clinical settings where AI models are deployed, as it enhances the trustworthiness of model outputs, aiding healthcare professionals in making informed decisions [91, 20]. Integrating clinical concepts into AI models, as suggested by [92], improves transparency and interpretability, fostering clinical trust and facilitating AI analyses' incorporation into routine practice.

Future research should focus on developing privacy-preserving techniques and improving data-sharing mechanisms to enhance AI models' robustness and reliability in healthcare. Addressing challenges related to non-IID data distributions is crucial for ensuring AI models' generalizability across diverse clinical settings [90]. By advancing data augmentation and uncertainty quantification, researchers can unlock AI's full potential in healthcare, ultimately improving patient outcomes and advancing personalized treatment strategies.

9 Conclusion

The application of artificial intelligence (AI) and machine learning (ML) in healthcare has revolutionized tumor diagnosis and precision oncology, significantly improving diagnostic accuracy and treatment methodologies. The adoption of deep learning-based computer-aided diagnosis (CAD) systems has notably enhanced breast cancer detection by reducing dependence on manual feature extraction and facilitating early diagnosis. Convolutional Neural Networks (CNNs) have demonstrated remarkable success in mammogram classification, achieving high precision in early breast cancer identification.

Innovative multimodal approaches, such as co-learning pipelines, exemplify the integration of clinical and imaging data to improve lung cancer detection accuracy. Models like D-Cube have set new benchmarks in medical imaging through advanced feature extraction and classification techniques. Nonetheless, challenges related to the transparency and interpretability of AI models persist, which are essential for their clinical adoption. The implementation of explainable AI (XAI) methods is crucial for building trust and comprehension in AI-driven diagnostics.

The variation in model performance across different datasets underscores the necessity for solutions that are generalizable across diverse clinical settings. Subgroup analysis is vital in identifying performance disparities and ensuring that AI models provide accurate and dependable diagnostic results. The integration of genomic data with imaging and clinical information is crucial for progressing precision oncology, requiring a comprehensive approach that includes genomics, transcriptomics, and functional analyses to enhance patient outcomes and develop tailored treatment strategies.

Future research should focus on creating hybrid models that utilize federated learning and transfer learning to address data privacy issues while improving computational efficiency. The continuous advancement of AI and ML technologies promises to further transform medical imaging analysis, leading to better patient outcomes and the progression of personalized treatment strategies in precision oncology. By addressing these challenges and fostering interdisciplinary collaboration, the transformative potential of AI in healthcare can be fully realized, ensuring its effective integration into clinical practice and enhancing patient care.

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