

# The Intersection of Remote Sensing and Biomedical Imaging: A Review of Techniques for Cancer Detection

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**Abstract**—Early and accurate cancer detection remains a major challenge in modern healthcare. This study explores the emerging intersection between biomedical imaging and remote sensing technologies, focusing on the adaptation of microwave radar, thermal imaging, multispectral imaging, and hyperspectral imaging (HSI) for non-invasive cancer diagnosis. Originally developed for environmental and aerospace applications, these technologies are now being repurposed to detect subtle biochemical, morphological, and metabolic changes in human tissues that signal the presence of cancer. When integrated with artificial intelligence and machine learning, these imaging modalities enable real-time classification, high-throughput analysis, and enhanced surgical guidance. We highlight their advantages over traditional imaging methods and examine their application in detecting malignancies of the brain, breast, skin, oral cavity, and gastrointestinal tract. This review also discusses critical clinical and technical challenges, including the lack of standardized datasets, issues with device mobility, data complexity, and regulatory hurdles. Finally, we outline promising future directions such as edge-based data processing, explainable AI systems, multimodal imaging fusion, and ethical considerations for deployment in resource-constrained settings. This multidisciplinary approach has the potential to revolutionize cancer diagnostics, making them faster, safer, and more accessible, particularly for underserved populations.

**Keywords**—Remote Sensing, Biomedical Imaging, Radar-Based Imaging, Thermal Imaging, Artificial Intelligence (AI), Cancer Detection

## I. INTRODUCTION

Cancer remains one of the leading causes of death worldwide, demanding the development of advanced diagnostic tools for early detection and effective treatment planning [1], [2]. Traditional biomedical imaging modalities such as magnetic resonance imaging (MRI), computed tomography (CT), ultrasound, and positron emission tomography (PET) have significantly contributed to cancer diagnostics [3], [4]. However, these modalities often require contrast agents, involve ionizing radiation, or lack the spectral sensitivity necessary to detect early biochemical changes in tissues [5]. In this context, remote sensing technologies originally designed for earth observation and environmental monitoring are now being explored for their potential to enhance biomedical imaging, particularly for cancer detection [6], [7].

Remote sensing involves the acquisition and interpretation of information about an object or area from a distance, typically through the analysis of electromagnetic radiation [8]. Key techniques in remote sensing such as multispectral imaging (MSI), hyperspectral imaging (HSI), and thermal infrared imaging offer high-resolution spatial and spectral data [9], [10]. These techniques have proven effective in detecting subtle spectral differences in natural terrains and vegetation, and their application to biomedical imaging enables the identification of cancerous tissues based on their distinct biochemical and morphological characteristics.

Recent interdisciplinary research highlights a growing convergence between remote sensing and biomedical imaging, with shared methodologies in image acquisition, feature extraction, pattern recognition, and machine learning-driven classification [11]. In particular, hyperspectral imaging capable of acquiring hundreds of narrow spectral bands can capture the molecular composition of tissues, allowing clinicians to distinguish between healthy and malignant cells without invasive procedures. These capabilities are highly valuable in cancer detection, where early-stage changes at the cellular level may not be visible through conventional imaging.

Furthermore, advanced image processing techniques from remote sensing, such as dimensionality reduction, spectral unmixing, and supervised classification, are being repurposed for clinical diagnostics [12]. The use of machine learning algorithms initially developed for satellite image analysis now supports real-time tumor classification and treatment monitoring [13]. In the strategic adaptation of high-spectral-resolution sensing and remote image processing pipelines to overcome the spectral insensitivity, radiation exposure, and invasiveness of conventional imaging systems. This cross-pollination of technologies fosters innovation and provides a pathway toward more accurate, efficient, and non-invasive diagnostic solutions. This review aims to provide a comprehensive synthesis of how remote sensing technologies are being re-engineered for biomedical imaging, with a focus on their application in cancer detection. It explores the fundamental principles of these technologies, presents clinical case studies, evaluates the integration of artificial intelligence, and identifies current challenges alongside future directions. By explicitly bridging the domains of

environmental remote sensing and medical diagnostics, this work contributes a novel interdisciplinary perspective that advances the frontier of precision healthcare.

## II. BACKGROUND OF THIS STUDY

The diagnosis of cancer has benefited greatly by the use of conventional biomedical imaging techniques such as positron emission tomography (PET), computed tomography (CT), ultrasound, and magnetic resonance imaging (MRI) [14]. These techniques, however, often include ionizing radiation, contrast chemicals, or lack the spectral sensitivity required to identify early metabolic alterations in tissues [15]. Originally created for environmental monitoring and earth observation, remote sensing technologies are currently being investigated for their potential to improve biomedical imaging, especially for the diagnosis of cancer [16]. The process of gathering and analyzing data about a thing or region from a distance, usually by analyzing electromagnetic radiation, is known as remote sensing [17]. High-resolution spatial and spectral data is provided by essential remote sensing methods as thermal infrared imaging, multispectral imaging (MSI), and hyperspectral imaging (HSI) [18], [19]. The use of these methods in biomedical imaging allows the diagnosis of malignant tissues based on their unique biochemical and physical traits, and they have shown efficacy in identifying minor spectrum changes in natural terrains and flora.

## III. REMOTE SENSING TECHNOLOGY

Using sensors that pick up reflected or emitted electromagnetic radiation, remote sensing is the process of gathering data about an object or phenomenon without actually being there [20]. Several remote sensing methods have been modified from their conventional environmental applications to biomedical imaging in the context of cancer diagnosis, providing special capabilities for collecting the thermal, structural, and biochemical properties of living tissues [21]. Fig. 1, shows how satellites use reflected electromagnetic radiation from the Earth's surface to collect remote sensing data for environmental, urban, and resource monitoring. Thermal infrared imaging (TIR), hyperspectral imaging (HSI), and multispectral imaging (MSI) are among the fundamental technologies [22].

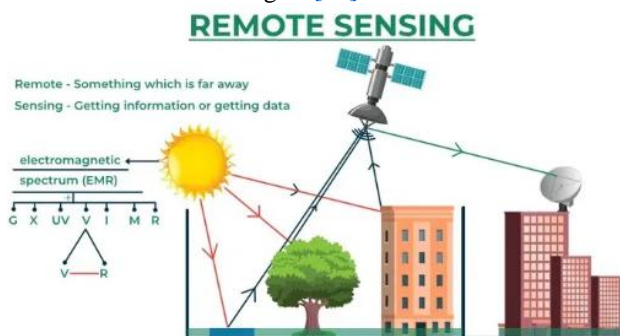


Fig. 1. Basic working principle of remote sensing using electromagnetic radiation [23]

Multispectral Imaging (MSI): Data at a few distinct spectral bands, usually between three and ten, are captured via multispectral imaging [24]. MSI is used in environmental research to track urban growth, categorize vegetation, and evaluate soil health. MSI is used in biomedical imaging to get

spectral information from tissues by using certain wavelengths that correlate to blood perfusion, cellular absorption, and oxygenation. Because various tissue types absorb and reflect light in different ways, MSI systems may differentiate between regions that are healthy and those that are not.

Hyperspectral Imaging (HSI): Through the capture of pictures over hundreds of continuous spectral bands, often in the 400–1000 nm range, HSI offers a large amount more spectral information than MSI [25]. This allows the spectral signals of tissues to be precisely identified in terms of their chemical makeup. Crop monitoring, water quality evaluation, and mineral mapping are all common applications of HSI in remote sensing. With simultaneous rich spatial and spectral information, HSI becomes an effective non-invasive tissue characterization tool when used to biomedical applications. HSI datasets often exceed 100GB per scan, requiring GPU clusters.

Thermal Infrared Imaging (TIR): To monitor temperature changes, thermal imaging records the infrared light that things produce [26]. TIR is used in remote sensing to monitor forest fires, identify heat loss in structures, and evaluate volcanic activity. Thermal imaging detects abnormal heat patterns from elevated blood flow and metabolism, often signaling early cancer.

## IV. BIOMEDICAL IMAGING MODALITIES

Biomedical imaging plays a crucial role in the diagnosis, staging, treatment planning, and monitoring of cancer [27]. These modalities enable visualization of anatomical structures, tissue functionality, and physiological processes in both invasive and non-invasive manners. While conventional imaging techniques such as MRI, CT, PET, and ultrasound remain foundational, newer imaging approaches particularly those enhanced by spectral and thermal information are being rapidly adopted due to their ability to reveal biochemical and metabolic characteristics associated with malignancy.

- Magnetic Resonance Imaging (MRI): MRI uses radio waves and powerful magnetic fields to produce high-resolution, three-dimensional pictures of soft tissue features [28]. It is commonly used to identify cancers of the brain, spine, breast, and prostate. Its capacity to identify alterations in tissue density and perfusion, which are suggestive of tumor activity, has been improved by diffusion-weighted imaging (DWI) and functional magnetic resonance imaging (fMRI).
- Computed Tomography (CT): CT scans provide cross-sectional pictures of the body using X-ray technology, often with the addition of contrast chemicals [29]. They are essential for identifying malignancies of the liver, pancreas, lungs, and bones. However, because of its poor soft tissue contrast, CT may not identify extremely early-stage cancers and exposes patients to ionizing radiation. In order to provide multi-layered diagnostics that integrate both anatomical and molecular information, research is being conducted to fuse CT data with spectral imaging methods.
- Positron Emission Tomography (PET): Tumors have higher glucose absorption, PET imaging, which utilizes radiotracers to monitor metabolic processes, is very

successful in detecting malignant cells [30]. A common method for evaluating cancer therapy and staging is combined PET/CT. Despite providing functional information, PET's spatial resolution is somewhat limited. By providing supplementary information, multispectral imaging may improve PET's accuracy in identifying lesions and tracking metabolic changes.

- **Ultrasound Imaging:** Ultrasound is a cost-effective, real-time imaging method commonly used in breast, liver, and thyroid cancer diagnostics [31]. It operates by transmitting sound waves and analyzing their echoes to produce images. However, it is operator-dependent and limited by acoustic shadowing and low contrast in some tissues. Recent innovations involve integrating ultrasound with thermal and spectral imaging especially in portable point-of-care devices.

## V. INTEGRATION OF REMOTE SENSING AND BIOMEDICAL IMAGING

The integration of remote sensing techniques with biomedical imaging represents a powerful multidisciplinary frontier for achieving more precise, non-invasive, and real-time cancer diagnosis [32], [33]. Although these two disciplines have historically developed separately, they have fundamental technological similarities, including the gathering of multispectral and hyperspectral data, image registration, feature extraction, and classification [34]. In Fig. 2, illustrates how diverse health data modalities integrate to enable opportunities in digital health, including precision medicine, virtual care, pandemic monitoring, and personalized digital health solutions. Opportunities for the cross-application of remote sensing techniques in the biomedical field are made possible by this common framework, especially in the areas of malignant tissue detection, characterization, and monitoring.

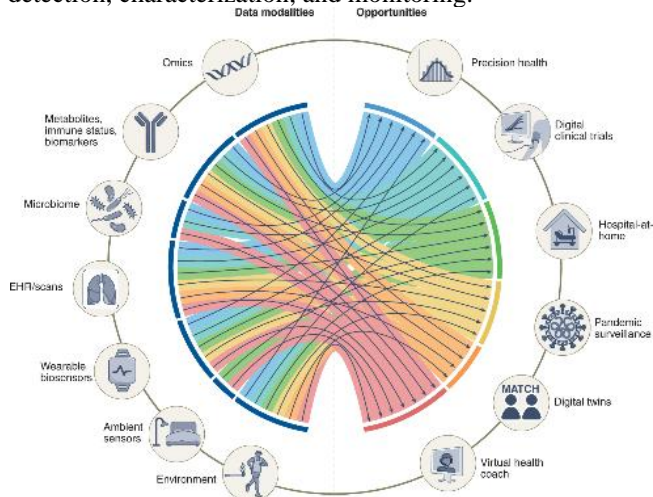


Fig. 2. Integration of multimodal health data and its opportunities in digital health [35]

## VI. HYPERSPECTRAL IMAGING FOR TISSUE CHARACTERIZATION

A sophisticated optical imaging method called hyperspectral imaging (HSI) records a broad range of light spanning hundreds of distinct and adjacent spectral bands [36]. In contrast to traditional imaging, which only records the three broad bands of red, green, and blue, HSI gives each

pixel in an image a complete spectrum profile, or “spectral signature.” HSI is a potent technique for tissue characterization and cancer detection because of the abundance of spectrum information it provides, which allows for in-depth examination of the biochemical and morphological characteristics of tissues [37].

- The cellular structure, water content, oxygenation, and molecular makeup of each biological tissue determine its own spectral reflectance pattern. In terms of vascularization, metabolism, and chemical makeup, cancerous tissues are very different from healthy ones. By monitoring how tissues absorb and reflect light at various wavelengths, especially in the visible spectrum, HSI may identify these variations.
- Intraoperative HSI allows real-time mapping of tumor margins, helping neurosurgeons avoid both excessive tissue removal and incomplete tumor resection. HSI has shown promise in differentiating malignant from benign lesions during lumpectomies by analyzing vascular patterns and tissue oxygenation.
- HSI data is high-dimensional, often containing hundreds of features per pixel. This necessitates sophisticated data processing methods to reduce dimensionality, remove noise, and extract relevant features. Which is, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), Support Vector Machines (SVMs) and Random Forests.

## VII. RADAR-BASED IMAGING FOR BREAST CANCER

Radar-based imaging, particularly microwave imaging, is an emerging non-invasive diagnostic technique that applies the principles of radar technology to detect and localize tumors, especially in breast tissue. Unlike conventional imaging modalities such as mammography or MRI, radar-based methods exploit the dielectric contrast between cancerous and normal tissues using low-power electromagnetic waves in the microwave frequency range (0.5–10 GHz) [38]. This technique offers several advantages including safety, portability, low cost, and the absence of ionizing radiation.

- **Principle of Radar-Based Imaging:** The differential dielectric characteristics of biological tissues provide the basis of radar-based imaging [39]. Malignant breast tumors richer in water and packed with dense cellular architecture exhibit a markedly higher dielectric constant and conductivity than surrounding adipose or fibroglandular tissue, producing a distinctive scattering signature when probed with low-frequency microwave energy.
- **Applications in Breast Cancer Detection:** The relatively uniform composition and peripheral anatomical location of the breast make microwave radar-based imaging especially well-suited for the diagnosis of breast cancer [40]. Studies in both preclinical and clinical settings have shown its promise for:
  - **Early Detection:** The high contrast in dielectric properties between malignant and normal tissues allows for the identification of tumors as small as a few millimeters.
  - **Safe Screening Alternative:** Since it uses non-ionizing radiation, it is safer than mammography and can be

used more frequently, including in younger women and those with dense breast tissue.

- Portable Screening Tools: Several research prototypes and startup solutions have proposed portable radar-based breast screening devices for use in rural and resource-limited settings.

### VIII. AI AND MACHINE LEARNING IN REMOTE SENSING-BASED CANCER DIAGNOSTICS

The integration of artificial intelligence (AI) and machine learning (ML) with remote sensing-based imaging modalities has accelerated the development of intelligent, automated systems for cancer detection [41]. The high dimensionality and complexity of hyperspectral, multispectral, and radar-based imaging data present significant challenges in manual interpretation. AI techniques, particularly deep learning models, provide the computational power and analytical precision needed to extract meaningful diagnostic insights from these data-rich imaging sources [42].

- Role of AI in Spectral and Radar Imaging: Artificial intelligence (AI) plays a pivotal role in transforming complex spectral and radar imaging data into accurate, actionable insights for advanced cancer diagnostics [43]. Hyperspectral and radar-based imaging generate high-dimensional datasets, capturing subtle biochemical and structural differences in tissues. AI models, particularly deep learning algorithms like convolutional neural networks (CNNs), can extract relevant features and classify malignant versus healthy tissue with high accuracy [44]. These models, adapted from remote sensing, support automated, real-time decision-making, enhancing both diagnostic precision and clinical workflow efficiency. In radar imaging, AI processes scattering patterns based on dielectric contrast to detect tumors, especially in dense breast tissue. By bridging spatial, spectral, and temporal information, AI empowers non-invasive, intelligent cancer detection and continues to drive innovation in precision oncology.
- Common AI Techniques in Cancer Imaging: Deep learning models like convolutional neural networks (CNNs), which are often used to extract spatial and spectral information from hyperspectral and radar data, are common AI approaches in cancer imaging [45]. By identifying intricate patterns in high-dimensional information, these algorithms are able to correctly categorize tissues as either benign or cancerous. While maintaining diagnostic characteristics, dimensionality reduction techniques such as autoencoders and principle component analysis (PCA) aid in the simplification of hyperspectral data. Random forests and support vector machines (SVMs) are also used for tumor categorization. Transfer learning has grown in popularity recently because it makes it possible to modify already trained models from remote sensing for use in medicine, eliminating the requirement for extensive annotated datasets while enhancing model effectiveness and diagnostic performance.
- AI-Driven Diagnostic Workflow: Preprocessing stages like noise reduction and normalization are the first in AI-driven diagnostic processes for remote sensing-based cancer diagnosis [46]. The precise categorization of

tissues as benign or cancerous is subsequently made possible by machine learning algorithms that extract spectral and spatial information from imaging data. Decision-support systems that provide real-time visuals and diagnostic recommendations use these categorizations. AI is a crucial part of contemporary, non-invasive cancer imaging technologies because of this approach, which improves early detection, increases surgical accuracy, and lowers diagnostic mistakes.

### IX. THERMAL IMAGING FOR METABOLIC ACTIVITY

Thermography, another name for thermal imaging, is a non-invasive method that makes temperature maps of the skin's surface by detecting infrared radiation released by the body [47]. It is used in cancer diagnostics to locate areas of elevated metabolic activity, which often correlate to tumor development brought on by angiogenesis and elevated cellular metabolism. Thermal imaging is a powerful tool for the early detection of cancer, as malignant cells typically exhibit increased metabolic activity and blood flow, resulting in higher temperatures compared to surrounding healthy tissue. Thermal imaging doesn't use ionizing radiation as X-rays or CT scans do, and it may be done repeatedly without causing damage. Its diagnostic potential has been further increased by developments in image processing algorithms and infrared sensor sensitivity, which enable more accurate detection of aberrant thermal patterns linked to malignant activity.

### X. DATA FUSION AND MACHINE LEARNING

Machine learning and data fusion are essential for improving the diagnostic capabilities of cancer imaging based on remote sensing [48]. Data fusion combines information from multiple imaging modalities such as radar-based scans, MRI, thermal imaging, and hyperspectral imaging to deliver a comprehensive characterization of tissue properties. By integrating structural, functional, and spectral data, clinicians gain deeper insights into tumor morphology, metabolic activity, and biochemical composition, enabling more accurate and informed diagnostic decisions. This fused data is analyzed by machine learning techniques, especially deep learning models, which decrease redundancy, identify important patterns, and accurately categorize tissue states. To handle the complexity of multi-source data, methods like ensemble learning models and convolutional neural networks (CNNs) are used [49]. The combination of machine learning and data fusion greatly enhances diagnostic accuracy, promotes early cancer diagnosis, and facilitates non-invasive, real-time clinical decision-making.

### XI. APPLICATIONS IN CANCER DETECTION

The integration of remote sensing methodologies into biomedical imaging has opened new avenues for enhancing cancer diagnostics [50]. By leveraging advanced imaging technologies and analytical tools initially developed for geospatial analysis, researchers can achieve more accurate, non-invasive, and real-time cancer detection. Below are key application areas where this interdisciplinary approach has demonstrated significant impact:

- Skin Cancer Detection: Hyperspectral and multispectral imaging, widely used in satellite surveillance, have been

- adapted to detect cutaneous malignancies. These imaging systems capture high-resolution spectral data across various wavelengths, enabling differentiation between benign and malignant lesions based on tissue reflectance patterns. Machine learning models trained on spectral signatures can classify lesion types with high accuracy, making these techniques particularly useful in dermatological screening.
- **Breast Cancer Diagnosis:** Microwave imaging, derived from radar-based remote sensing systems, provides a non-ionizing and cost-effective method for detecting breast tumors. This technique exploits dielectric contrast between healthy and cancerous tissues. When combined with AI-based pattern recognition and inverse scattering algorithms, microwave imaging can localize tumors even in dense breast tissue where traditional mammography may be less effective.
  - **Brain Tumor Segmentation:** Advanced segmentation algorithms originally developed for terrain classification in remote sensing are now used to delineate tumor boundaries in magnetic resonance imaging (MRI) of the brain. Techniques such as convolutional neural networks (CNNs), support vector machines (SVMs), and region-growing methods enhance precision in identifying tumor margins, aiding in surgical planning and therapy monitoring.
  - **Lung Cancer Screening:** Computed tomography (CT) images of the lungs benefit from 3D image reconstruction and visualization techniques pioneered in satellite imagery. These methods allow for detailed volumetric analysis of nodules, improving early detection of lung cancer. Spectral CT imaging, analogous to hyperspectral remote sensing, offers additional diagnostic value by analyzing energy-dependent tissue attenuation.
  - **Gastrointestinal and Oral Cancers:** Endoscopic imaging enhanced with multispectral sensing technologies is being explored for early detection of esophageal, gastric, and oral cancers. These systems provide enhanced contrast and depth information, enabling clinicians to identify precancerous lesions with improved confidence.

## XII. CHALLENGES AND LIMITATIONS

While combining biomedical imaging with remote sensing has enormous potential to improve cancer diagnosis, a number of obstacles prevent its broad clinical use. The amount and complexity of hyperspectral, thermal, and radar imaging data are significant issues as they need sophisticated algorithms and a lot of computing power for real-time processing and interpretation. Furthermore, the dependability and generalizability of machine learning models are diminished by the absence of defined procedures and annotated clinical datasets. Deployment in standard clinical and point-of-care settings is further limited by hardware constraints, such as the size and expense of imaging equipment. Concerns have also been raised over AI models' "black-box" character, which makes it difficult for doctors to completely trust or understand diagnostic results. Lastly, to guarantee the safe, fair, and open use of these technologies in healthcare, ethical and legal concerns including algorithmic bias, patient consent, and data privacy must be addressed.

- High-dimensional spectral and radar imaging data require advanced processing capabilities not always available in clinical settings.
- Inconsistent imaging techniques and absence of large, annotated clinical datasets hinder reproducibility and validation of AI models.
- Remote sensing-derived imaging systems are often too bulky or costly for point-of-care or low-resource healthcare environments.
- Deep learning models lack explainability, reducing clinical confidence and making medical decision support harder to justify.
- Issues surrounding data security, patient privacy, and compliance with health regulations must be carefully managed.
- Seamless adoption into existing diagnostic pathways and surgical procedures remains technically and logistically difficult.

## XIII. FUTURE DIRECTION

Although the field of cancer diagnosis is still in its infancy, the combination of remote sensing and biomedical imaging has enormous potential for advancement and influence. Future studies will concentrate on shrinking remote sensing devices, such as hyperspectral and radar-based imaging systems, so they may be easily incorporated into clinical settings, such as operating rooms and point-of-care settings. A major challenge moving forward will be the creation and standardization of large, annotated clinical datasets that reflect diverse cancer types and patient populations. These datasets are essential for training robust machine learning models with high generalizability. By providing clear, interpretable models, deep learning advancements especially in explainable AI will increase clinician confidence. Creating extensive, diversified, and annotated clinical datasets will also be essential for training machine learning algorithms that are reliable and generalizable across cancer kinds and populations. Fusion of multimodal imaging integrating anatomical, spectral, thermal, and functional data into unified diagnostic platforms is another important avenue. To support real-time image analysis and decision-making, especially in low-resource or mobile screening environments, cloud computing and edge AI will become increasingly important. However, achieving consistent performance across varied hardware and network conditions will remain a key technical challenge. Lastly, concurrent development of ethical frameworks and regulatory policies is necessary to guarantee privacy, equity, and responsibility in the application of these technologies in actual healthcare systems.

- Develop compact, portable remote sensing devices tailored for use in operating rooms and clinics.
- Advance interpretable machine learning models to support transparent, clinician-friendly decision-making.
- Integrate hyperspectral, thermal, MRI, and radar data into unified diagnostic tools for a more holistic cancer assessment.
- Leverage cloud and edge computing to enable fast, local analysis in low-resource or mobile screening environments.

- Build diverse, annotated databases to improve AI model accuracy and generalizability across different patient populations.

#### XIV. CONCLUSION

In terms of early cancer detection and diagnosis, the nexus of biomedical imaging and remote sensing provides a revolutionary horizon. This interdisciplinary approach uses technologies like radar-based systems, thermal imaging, and hyperspectral imaging to provide strong tools that may reveal biochemical, structural, and metabolic changes in tissues often before obvious morphological indicators show. These technologies may enable real-time clinical decision-making, automate and improve diagnostic accuracy, and lessen need on invasive procedures when paired with AI and machine learning. Notwithstanding the encouraging developments, a number of obstacles still exist, such as the complexity of the data, hardware constraints, a lack of standards, and moral dilemmas. It will need developments in sensor design, algorithm transparency, and the creation of varied, annotated clinical datasets to get over these obstacles. Integrating explainable AI with multimodal imaging technologies, underpinned by strong legal frameworks that guarantee patient privacy and fair access, is the way of the future.

In this meta-analysis, the combination of biomedical imaging and remote sensing might transform cancer diagnosis by making it quicker, more precise, and available to all healthcare systems worldwide. The field of precision oncology is expected to undergo a transformation as research continues to close the gap between tailored medication and environmental monitoring.

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