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Transforming Oncology Imaging with Foundation Models for Intelligent Radiology Report Generation

*[1]Dr. Sneha T. Waghmare, [2]Dr. Meera N. Nair, [3]Dr. Arjun K. Verma, [4]Mr. Shatrughna U. Nagrik

[*1]Department of Clinical Pharmacy, Mumbai (MS), India, snehawaghmare.cp@gmail.com
[2]Department of Radiodiagnosis, Medical Imaging Centre, Kochi (KL), India, meeranair.radiology@gmail.com
[3]Department of Oncology, Cancer Care Institute, New Delhi (DL), India, arjunverma.oncology@gmail.com
[4]satyjeet college of pharmacy, Mehkar (MS), India, rahulnagrik96@gmail.com

ABSTRACT:

Radiology reports are the primary means of communication between radiologists and referring clinicians, providing essential information for disease diagnosis, treatment planning, therapeutic response assessment, and longitudinal patient management. In oncology, the increasing volume, complexity, and multimodal nature of imaging examinations have created a growing demand for reporting systems that are both accurate and efficient. Recent advances in artificial intelligence (AI), particularly the emergence of foundation models, have significantly transformed automated radiology report generation. Trained on large-scale multimodal datasets, foundation models learn generalized representations that can be adapted to a wide range of clinical tasks, enabling the generation of coherent, context-aware, and clinically meaningful radiology reports through the integration of medical imaging and natural language processing.

This review explores the evolution of automated radiology report generation, tracing its progression from traditional rule-based systems and convolutional neural network (CNN)-based approaches to transformer architectures, vision-language models, and multimodal large language models (LLMs). Particular emphasis is placed on their applications in oncology imaging, including computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and hybrid imaging modalities. The review further examines major foundation model architectures, publicly available datasets, evaluation benchmarks, clinical applications, and the advantages and limitations of current methodologies. In addition, key challenges associated with clinical implementation—including model hallucination, limited explainability, data heterogeneity, privacy protection, regulatory compliance, and the need for rigorous prospective validation—are critically discussed.

Current evidence indicates that foundation models outperform earlier AI-based approaches by improving report quality, contextual understanding, linguistic coherence, and cross-domain generalizability. Nevertheless, several technical and clinical challenges must be addressed before these systems can be safely integrated into routine oncology practice. Future research should prioritize the development of domain-specific multimodal foundation models, federated learning frameworks for privacy-preserving collaboration, explainable AI techniques to enhance clinical trust, and large-scale prospective validation studies. As these technologies continue to mature, foundation models have the potential to transform radiology workflows by improving reporting efficiency, consistency, diagnostic accuracy, and clinical decision support, ultimately contributing to more precise and personalized cancer care.

Keywords: Foundation models; Automated radiology report generation; Oncology imaging; Large language models; Vision-language models; Artificial intelligence; Medical imaging; Precision oncology.

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1. Introduction

Medical imaging is fundamental to modern oncology, serving a pivotal role in cancer detection, diagnosis, staging, treatment planning, therapeutic response assessment, and long-term disease surveillance [1,2]. Imaging modalities such as computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and hybrid imaging generate vast amounts of diagnostic information that must be synthesized into accurate and clinically meaningful radiology reports. These reports represent the primary communication channel between radiologists and referring clinicians, guiding critical decisions throughout the continuum of cancer care. However, the continuous growth in imaging volume, increasing examination complexity, global shortages of radiologists, and the need for standardized, high-quality reporting have intensified the demand for intelligent automated reporting solutions [3].

Early attempts at automated radiology report generation relied primarily on handcrafted features, predefined templates, and rule-based expert systems. Although these approaches demonstrated feasibility, they were constrained by limited scalability, poor adaptability, and an inability to capture the complexity and variability of clinical language. The rapid evolution of deep learning subsequently introduced convolutional neural networks (CNNs), which enabled automatic extraction of high-level imaging features and significantly improved computer-aided image interpretation. More recently, transformer architectures and large-scale foundation models have revolutionized artificial intelligence by leveraging self-supervised pretraining on massive multimodal datasets, enabling powerful transfer learning capabilities across diverse medical imaging and language tasks [4].

Foundation models—including Vision Transformers (ViTs), multimodal transformers, vision-language models (VLMs), and large language models (LLMs)—have demonstrated unprecedented performance in image understanding, clinical language generation, multimodal reasoning, and contextual knowledge integration. Their ability to jointly process visual and textual information makes them particularly well suited for oncology imaging, where accurate interpretation often requires the integration of anatomical, functional, molecular, and longitudinal clinical information across multiple imaging modalities [5]. Consequently, foundation models are emerging as a transformative technology capable of improving reporting efficiency, diagnostic consistency, clinical decision support, and personalized cancer management.

This review provides a comprehensive overview of the evolution of automated radiology report generation, with particular emphasis on the emergence and application of foundation models in oncology imaging. It critically examines major model architectures, publicly available datasets, evaluation methodologies, clinical applications, current limitations, and future research directions, highlighting the opportunities and challenges associated with integrating foundation models into routine oncologic radiology practice.

2. Foundation Models in Medical Imaging

Foundation models are large-scale neural networks pretrained on massive and diverse datasets using self-supervised or weakly supervised learning paradigms. Unlike conventional task-specific models that are optimized for a single application, foundation models learn generalized and transferable feature representations that can be efficiently adapted to a broad range of downstream tasks with minimal fine-tuning [6]. This capability has transformed artificial intelligence by enabling the development of versatile models that perform effectively across image analysis, natural language processing, multimodal reasoning, and clinical decision-support applications.

Several foundation model architectures have become particularly influential in medical imaging, including:

- Vision Transformers (ViTs)
- Contrastive Language–Image Pretraining (CLIP)
- Bidirectional Encoder Representations from Transformers (BERT)
- Generative Pretrained Transformers (GPT)
- Medical-domain multimodal foundation models integrating imaging and clinical language

The principal strength of foundation models lies in their ability to exploit large-scale multimodal datasets to learn rich semantic representations that capture complex relationships between visual information and textual descriptions. Within medical imaging, these models simultaneously learn anatomical structures, pathological features, disease progression patterns, and clinical terminology, enabling a more comprehensive understanding of imaging studies than traditional machine learning approaches [7]. Their capacity to integrate heterogeneous sources of information makes them particularly valuable in oncology, where accurate interpretation often depends on combining imaging findings with clinical context and longitudinal patient data.

Compared with conventional convolutional neural network (CNN)-based architectures, foundation models demonstrate substantially greater scalability, adaptability, and generalizability across diverse imaging tasks. Although CNNs remain highly effective for extracting local spatial features, they are inherently limited in modeling long-range spatial relationships and complex contextual dependencies. Transformer-based foundation models address these limitations through self-attention mechanisms that capture global interactions across entire images while effectively integrating multimodal information. Consequently, these models have achieved state-of-the-art performance in numerous medical imaging applications, including lesion detection, image classification, segmentation, visual question answering, and automated radiology report generation [8].

3. Evolution of Automated Radiology Report Generation

Automated radiology report generation has evolved through several technological phases.

3.1 Rule-Based Systems

Early automated radiology report generation systems were primarily based on predefined templates and expert-designed rule sets. These systems generated reports by matching detected imaging findings with predetermined phrases and reporting structures. Their main advantage was high interpretability, as every output could be traced back to specific rules created by domain experts. Additionally, they ensured consistency in report formatting and terminology. However, these approaches lacked flexibility and struggled to handle complex or unexpected clinical scenarios. Since they depended heavily on manually crafted rules, adapting them to new diseases, imaging modalities, or reporting styles was challenging. Consequently, their limited generalizability restricted widespread clinical applicability [9].

3.2 CNN-Based Encoder–Decoder Models

The introduction of deep learning significantly advanced the field of automated radiology report generation through the development of encoder–decoder architectures. In these systems, convolutional neural networks (CNNs) function as encoders that automatically extract meaningful visual features from medical images, such as chest X-rays, CT scans, or MRI images. Unlike traditional machine learning methods that rely on handcrafted features, CNNs learn hierarchical image representations directly from large datasets, enabling more accurate identification of anatomical structures and pathological abnormalities. The extracted image features are then passed to recurrent neural networks (RNNs), such as Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) networks, which act as decoders to generate descriptive textual reports.

One of the primary advantages of encoder–decoder architectures is their ability to perform automated feature extraction, reducing the need for manual intervention and expert-designed image descriptors. Additionally, these models are highly scalable and can be trained on large imaging datasets, allowing them to adapt to diverse reporting tasks. However, several limitations remain. RNN-based decoders often struggle to capture complex contextual relationships within medical images and reports. Their sequential processing nature makes it difficult to model long-term dependencies, leading to information loss in lengthy report generation tasks. Consequently, generated reports may lack clinical completeness and coherence, motivating the adoption of transformer-based and foundation-model approaches that better capture global contextual information and improve report quality [10].

3.3 Transformer-Based Architectures

The introduction of transformer architectures marked a significant advancement in automated radiology report generation. Unlike recurrent neural networks (RNNs), which process information sequentially, transformers employ self-attention mechanisms that enable the model to analyze all input features simultaneously. This capability allows transformers to capture both local and global relationships within medical images and associated textual information more effectively. Transformer Encoder–Decoder frameworks use an encoder to extract comprehensive image representations and a decoder to generate coherent and contextually relevant reports. By modeling long-range dependencies, transformers overcome the limitations of RNNs, which often struggle with information loss in lengthy sequences. As a result, transformer-based models produce reports with improved accuracy, consistency, and clinical relevance. Their ability to focus on important image regions through attention mechanisms enhances the description of abnormalities and disease patterns. Consequently, transformers have become the foundation of modern radiology reporting systems and have paved the way for the development of large multimodal foundation models. [11].

3.4 Foundation Models and Multimodal AI

Recent systems combine large-scale image encoders and language models. These architectures perform image interpretation, clinical reasoning, and report generation within a unified framework [12].
The transition from CNN-based systems to foundation models represents a paradigm shift from task-specific learning to generalized multimodal intelligence.

4. Application of Foundation Models in Oncology Imaging

Oncology imaging presents unique challenges due to tumor heterogeneity, longitudinal monitoring requirements, and multimodal data integration.

4.1 Computed Tomography

CT remains the most widely used modality for cancer staging and follow-up. Foundation models can identify lesions, quantify tumor burden, and generate structured reports describing disease extent [13].

4.2 Magnetic Resonance Imaging

MRI provides superior soft-tissue characterization. Foundation models have demonstrated promising performance in brain tumor characterization, prostate cancer assessment, and liver lesion evaluation [14].

4.3 PET and Hybrid Imaging

PET/CT and PET/MRI generate large amounts of functional and anatomical information. Automated reporting systems based on foundation models can integrate multimodal findings into coherent clinical narratives [15].

4.4 Longitudinal Cancer Monitoring

Foundation models are particularly valuable for comparing serial imaging studies and summarizing treatment responses according to standardized criteria such as RECIST [16].

5. Large Language Models and Vision-Language Models for Radiology Reporting

Large language models (LLMs) have emerged as a transformative technology in medical report generation due to their exceptional ability to understand and generate human-like text. Built on transformer architectures and trained on massive datasets, LLMs can capture complex linguistic patterns, medical terminology, and contextual relationships. In radiology, these models can convert imaging findings into coherent, structured, and clinically meaningful reports. Compared with traditional report generation methods, LLMs improve language fluency, consistency, and completeness. They can also integrate information from multiple sources, supporting more accurate clinical documentation. However, challenges such as hallucinations, bias, and explainability must be addressed before widespread clinical adoption.

5.1 Large Language Models

Models such as GPT-based architectures can generate fluent, contextually appropriate text. When combined with radiological image representations, they can produce reports that resemble those written by expert radiologists [17].

5.2 Vision-Language Models

Vision-language models (VLMs) integrate image analysis and natural language processing within a unified framework, enabling simultaneous understanding of visual and textual information. Examples include CLIP-inspired architectures and multimodal transformer models that learn associations between medical images and corresponding reports. In radiology, these models enhance automated report generation by accurately linking imaging findings with relevant clinical descriptions. A major advantage of VLMs is their improved alignment between visual features and textual content, resulting in more precise and clinically meaningful reports. They also improve report coherence by maintaining contextual consistency throughout the generated text. Furthermore, VLMs support advanced retrieval, summarization, and decision-support applications in medical imaging [18]

5.3 Comparative Analysis

Approach	Strengths	Limitations
CNN-based	Efficient feature extraction	Limited context
Transformer-based	Global attention	Data intensive

Foundation models	Transfer learning, scalability	High computational cost
Multimodal LLMs	Clinical reasoning, report quality	Hallucinations, explainability concerns

6. Datasets and Benchmarking Methods

The development and validation of automated radiology report generation systems depend on the availability of large, diverse, and well-annotated imaging datasets. High-quality datasets enable foundation models to learn meaningful associations between medical images and corresponding radiology reports while facilitating standardized benchmarking across different algorithms. Several publicly available datasets have become essential resources for training and evaluating AI models in medical imaging and oncology research.

Widely used datasets include:

- **MIMIC-CXR** – A large-scale chest radiography dataset containing hundreds of thousands of chest X-rays paired with corresponding radiology reports.
- **CheXpert** – A comprehensive chest radiograph dataset designed for automated disease classification and report generation tasks.
- **OpenI** – A publicly accessible collection of radiological images and associated clinical reports maintained by the National Library of Medicine.
- **PadChest** – A large annotated chest X-ray dataset containing extensive imaging findings and diagnostic labels suitable for multimodal AI development.
- **The Cancer Imaging Archive (TCIA)** oncology datasets – A diverse repository of cancer imaging data encompassing multiple tumor types, imaging modalities, and associated clinical information, supporting AI research in precision oncology.

  The performance of automated report generation models is commonly evaluated using natural language generation metrics, including:
- **BLEU (Bilingual Evaluation Understudy)**
- **ROUGE (Recall-Oriented Understudy for Gisting Evaluation)**
- **CIDEr (Consensus-based Image Description Evaluation)**
- **METEOR (Metric for Evaluation of Translation with Explicit Ordering)**
- **BERTScore**

These evaluation metrics primarily quantify the linguistic similarity between AI-generated reports and reference reports by assessing lexical overlap, semantic similarity, and contextual consistency. However, linguistic agreement alone does not necessarily reflect clinical accuracy or diagnostic reliability. Reports with high language similarity may still omit critical findings, introduce clinically significant errors, or generate misleading statements. Consequently, recent research increasingly emphasizes clinically oriented evaluation frameworks, including expert radiologist assessment, factual consistency analysis, disease-specific accuracy metrics, and prospective clinical validation studies to better determine the real-world utility and safety of automated reporting systems [19].

7. Clinical Applications and Benefits

Foundation-model-based reporting systems offer several clinical advantages.

Improved Efficiency

Automated report generation can reduce reporting time and alleviate radiologist workload [20].

Standardization

Structured reporting improves consistency across institutions and reduces inter-observer variability [21].

Decision Support

Foundation models can highlight abnormalities and suggest differential diagnoses, supporting clinical decision-making [22].

Automated summarization of tumor burden and treatment response may improve multidisciplinary cancer management [23].

Table 1. Representative Foundation Models for Automated Radiology Report Generation

Model	Year	Architecture	Dataset	Key Features	Limitations
BioViL	2022	Vision-Language Transformer	MIMIC-CXR	Cross-modal learning	Limited oncology-specific validation
GatorTron	2022	Large Language Model	Clinical Text Corpora	Clinical language understanding	Requires adaptation for imaging

Med-PaLM	2023	Medical LLM	Multisource Medical Data	Medical reasoning	Hallucination risk
LLaVA-Med	2024	Vision-Language Model	Biomedical Images	Multimodal interaction	Limited regulatory validation
Med-Gemini	2025	Multimodal Foundation Model	Multimodal Medical Data	Integrated reasoning	Computational complexity

8. Challenges and Limitations

Despite significant advancements in automated radiology report generation, hallucinations remain a major challenge in large language models (LLMs). Hallucinations occur when a model generates information that appears plausible and linguistically correct but is not supported by the actual medical image or clinical data. In radiology, such errors may include reporting nonexistent abnormalities, omitting important findings, or providing inaccurate clinical interpretations. These mistakes can compromise diagnostic accuracy and patient safety, limiting the reliability of fully automated reporting systems. Therefore, robust validation methods, multimodal verification mechanisms, and human oversight by radiologists are essential to ensure the clinical accuracy and trustworthiness of AI-generated reports.[24].

Data Heterogeneity

Hallucinations represent one of the most critical limitations of large language models used in automated radiology report generation. A hallucination occurs when the model produces information that is not supported by the input medical image or clinical data. Although the generated text may appear accurate and convincing, it can contain incorrect findings, missed abnormalities, or fabricated clinical details. In oncology imaging, such errors may affect diagnosis, staging, and treatment decisions, potentially compromising patient care. Reducing hallucinations requires improved multimodal training, rigorous validation, explainable AI techniques, and continuous human supervision. Therefore, radiologist oversight remains essential for ensuring report accuracy and clinical reliability.[25].

Limited Explainability

Many foundation models operate as "black-box" systems, meaning their internal decision-making processes are difficult for clinicians to interpret and understand. Although these models can achieve high performance in image analysis and report generation, they often provide limited explanations for how specific conclusions or recommendations are derived. This lack of transparency can reduce clinician confidence and hinder the adoption of AI systems in routine clinical practice. In oncology imaging, where diagnostic decisions directly influence patient management, explainability is particularly important. Developing interpretable AI methods, attention visualization tools, and transparent decision-support mechanisms is essential to improve trust, accountability, and safe clinical implementation.[26].

Computational Requirements

One of the major challenges associated with foundation models in radiology is their substantial computational requirement. Training these large-scale models typically involves billions of parameters and requires access to high-performance computing infrastructure, including advanced graphics processing units (GPUs), tensor processing units (TPUs), extensive memory, and large-scale storage systems. The training process can be time-consuming and expensive, making it difficult for smaller healthcare institutions and research centers to develop or fine-tune such models independently. Additionally, deploying foundation models in clinical settings requires significant computational resources to ensure rapid and reliable report generation. These infrastructure demands can create accessibility barriers, particularly in low-resource environments and developing regions. Furthermore, increased energy consumption and operational costs raise concerns regarding sustainability. Therefore, developing more efficient model architectures, optimization techniques, and cloud-based deployment strategies is essential to improve accessibility and facilitate broader adoption of foundation-model-based radiology reporting systems [27].

9. Ethical, Regulatory, and Privacy Considerations

The clinical implementation of foundation models in radiology requires careful consideration of ethical, legal, and regulatory issues. Protecting patient privacy and ensuring data security are essential due to the sensitive nature of medical information used for model training and deployment. Algorithmic bias may arise from unrepresentative datasets, potentially leading to unequal performance across different patient populations. Another critical concern is accountability when AI-generated reports contain errors that affect clinical decisions. Additionally, compliance with healthcare regulations and medical device standards is necessary before clinical adoption. Consequently, healthcare authorities increasingly emphasize transparent validation, continuous performance monitoring, and post-deployment surveillance to ensure safe and responsible AI implementation[28].

10. Future Perspectives and Research Directions

Future research in automated radiology report generation should focus on developing oncology-specific foundation models trained on diverse cancer imaging datasets to improve disease-specific performance and clinical relevance. Federated learning frameworks can facilitate collaboration among institutions while preserving patient privacy and data security. Explainable multimodal AI systems are needed to enhance transparency and clinician trust by providing interpretable reasoning behind generated reports. Integrating genomic, pathological, and imaging data may support more comprehensive and personalized cancer assessment. Additionally, prospective multicenter clinical trials are essential to validate model performance across different healthcare settings and patient populations. Real-time clinical deployment studies should evaluate workflow integration, efficiency, and patient outcomes. Furthermore, human–AI collaborative reporting systems that combine the strengths of artificial intelligence and radiologist expertise may improve report accuracy, reduce workload, and promote safer adoption of AI technologies in oncology imaging.

11. Conclusion

Foundation models represent a major advancement in automated radiology report generation. By integrating visual understanding, language generation, and multimodal reasoning, these systems offer substantial improvements over traditional CNN-based and transformer-based approaches. In oncology imaging, foundation models have the potential to enhance reporting efficiency, standardization, and clinical decision support. However, challenges related to hallucination, explainability, data diversity, and regulatory approval remain significant. Continued interdisciplinary collaboration among radiologists, oncologists, computer scientists, and regulatory bodies will be essential for realizing the full clinical potential of foundation-model-driven radiology reporting.

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