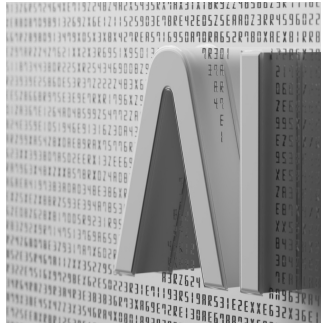

Transforming Radiology Reporting with Large Language Models



Structured reporting (SR) in radiology aims to standardise and enhance the quality of radiological reports, improving consistency, clarity and adherence to guidelines. Despite the recognised benefits, implementing SR widely has proven challenging. Traditional methods of SR often require considerable effort to create, maintain and update templates. However, recent advancements in large language models (LLMs) are creating opportunities to automate and refine SR processes in radiology.

Evolution of Structured Reporting in Radiology

The need for standardised reporting in radiology has been discussed for nearly a century, with early calls advocating consistency in terminology and reporting practices. Over the years, organisations such as the American College of Radiology (ACR) and the Radiological Society of North America (RSNA) have significantly promoted SR. The introduction of tools like RadLex® and the RadReport Template Library aimed to unify radiological lexicons and reporting formats. In 2018, the European Society of Radiology (ESR) published guidelines advocating for international collaboration to support the implementation of SR.

Despite these efforts, traditional SR methods remain largely dependent on manual processes, requiring radiologists to invest significant time in creating detailed and standardised reports. This rigidity, coupled with the high workload, has limited the broader adoption of SR. However, advances in information technology have gradually introduced new possibilities, with LLMs presenting a breakthrough that could reshape radiology reporting.

Capabilities of Large Language Models in Radiology Reporting

Large language models, particularly those based on transformer architectures, have shown remarkable potential in automating SR in radiology. LLMs like GPT-3.5 and GPT-4 can effectively transform free-text radiological reports into structured formats, reducing errors and improving consistency. These models are designed to interpret vast amounts of data and recognise complex linguistic patterns, allowing them to accurately generate structured outputs that align with standard reporting guidelines.

One of the key advantages of LLMs is their ability to understand and contextualise language, which makes them well-suited to process medical information. These models can automate documentation, translation and summarisation tasks, thereby enhancing radiologists' efficiency. Studies have demonstrated their ability to convert free-text reports into structured formats, improving adherence to guidelines and ensuring a more comprehensive presentation of medical findings. Additionally, the multilingual capabilities of some LLMs enable them to generate structured reports in various languages, broadening their applicability in diverse clinical settings.

However, despite their advantages, LLMs are not without limitations. A significant challenge is the tendency of LLMs to produce "hallucinations," where the model generates incorrect or entirely fictitious information. These errors can stem from biases or gaps in the training data, potentially impacting the quality and accuracy of the generated reports. Furthermore, while LLMs can effectively handle structured formats, their understanding of specialised medical terminology and nuanced interpretations remains a work in progress.

Challenges and Regulatory Considerations

While LLMs offer promising avenues for transforming SR, several challenges must be addressed to ensure their successful integration into clinical practice. One of the primary concerns is the explainability of AI-generated reports. Understanding the rationale behind a decision is crucial for maintaining trust and accountability in clinical settings. The opaque nature of many AI models makes it difficult for healthcare professionals to verify and justify the generated outputs. As such, enhancing transparency and interpretability remains a critical area of focus.

Furthermore, integrating LLMs into clinical workflows raises important questions about regulatory compliance. Many regions are in the process of developing legal frameworks for AI in healthcare, but progress varies significantly. In the United States, for instance, AI-driven medical products are subject to standard approval processes by the Food and Drug Administration (FDA). In contrast, the European Union is gradually establishing specific guidelines for AI-based healthcare solutions. These regulatory developments are essential to ensure that AI systems used in clinical settings meet safety, efficacy and ethical standards.

Another challenge is the need to address biases in training data. LLMs are trained on vast datasets, and biases inherent in these datasets can influence the model's outputs. This is particularly relevant in medical AI, where biases can significantly affect patient care. Additionally, LLMs must be continually updated with the latest medical knowledge to avoid the dissemination of outdated or incorrect information. Solutions such as integrating external knowledge bases and implementing human-in-the-loop systems are being explored to improve the reliability and accuracy of LLM outputs.

Large language models have the potential to revolutionise structured reporting in radiology by automating the conversion of free-text reports into structured formats, improving accuracy and consistency. The adoption of LLMs in radiology reporting can address many of the challenges associated with traditional SR methods, enhancing efficiency and facilitating better patient outcomes. However, several obstacles remain, including the explainability of AI-generated outputs, the presence of biases and the development of appropriate regulatory frameworks.

Moving forward, it is crucial to refine these models to minimise errors and ensure that their outputs are transparent and reliable. Collaboration between AI developers, radiologists and regulatory bodies will be key to achieving these goals. With ongoing advancements and strategic efforts, LLMs could be central in standardising radiology reporting and enhancing clinical practice.

Source: [European Radiology](#)

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