Harnessing Knowledge Retrieval with Large Language Models for Clinical Report Error Correction

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Abstract

This study proposes an approach for error correction in clinical radiology reports, leveraging large language models (LLMs) and retrievalaugmented generation (RAG) techniques. The proposed framework employs internal and external retrieval mechanisms to extract relevant medical entities and relations from the report and external knowledge sources. A three-stage inference process is introduced, decomposing the task into error detection, localization, and correction subtasks, which enhances the explainability and performance of the system. The effectiveness of the approach is evaluated using a benchmark dataset created by corrupting real-world radiology reports with realistic errors, guided by domain experts. Experimental results demonstrate the benefits of the proposed methods, with the combination of internal and external retrieval significantly improving the accuracy of error detection, localization, and correction across various state-of-the-art LLMs. The findings contribute to the development of more robust and reliable error correction systems for clinical documentation.

1 Introduction

The rise of large language models (LLMs) have brought significant advancements to healthcare, with one of the fastest-growing applications being the generation of clinical notes (Abacha et al., 2023a; Zhou et al., 2023; Rajpurkar et al., 2022). However, guaranteeing the quality and accuracy of these AI-generated notes remains a challenge, as LLMs may occasionally produce hallucinated content that deviates from factual information (Ji et al., 2023; Guerreiro et al., 2023). Similarly, reports manually written by radiologists are not immune to errors, underscoring the need for meticulous error correction to achieve accurate clinical documentation, which is paramount for ensuring

effective communication among healthcare professionals and ultimately, optimal patient care (Wu et al., 2022; Brady, 2017; Brady et al., 2021).

Current research on clinical report error correction is quite limited. The MEDIQA-CORR 2024 shared task (Ben Abacha et al., 2024) attempts to evaluate the potential of using LLMs as solutions to locate and correct medical errors within clinical notes(Achiam et al., 2023; Touvron et al., 2023). However, their study is limited by the use of synthetic data rather than real-world clinical notes, reducing its practicality in clinical settings. Furthermore, the task of error correction in clinical reports is inherently complex, requiring a large language model with strong command capabilities, as well as extensive clinical knowledge and reasoning skills.

In a clinical setting with limited computational resources, training a large, instruction-fine-tuned model specifically for this task may be impractical. To address this challenge, we propose a more feasible approach that guides the model to better perform the task by adjusting the instructions and enhancing context extraction. Our method leverages the strengths of existing LLMs while mitigating their limitations through a three-stage framework and retrieval-augmented generation (RAG) techniques.

The three-stage approach decomposes the error correction process into distinct subtasks: error detection, error localization, and error correction. By breaking down the complex task into more manageable and interpretable steps, we aim to improve the overall performance and explainability of the system, enabling a more comprehensive understanding of the error correction pipeline. This approach allows the model to focus on each subtask independently, leveraging the strengths of LLMs while mitigating their inherent limitations in the context of medical error detection and correction.

Furthermore, we introduce a retrieval-

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augmented generation (RAG) approach for clinical report error correction, which retrieves medical entities and relations both internally and externally to facilitate contextual and comprehensive reasoning. The purpose of internal retrieval is to detect inconsistencies within the provided report, whereas external retrieval seeks to augment the reasoning process when the given report lacks adequate contextual information.

To rigorously evaluate the performance of our proposed approach, we establish a benchmark for the clinical report error detection task by intentionally introducing common mistakes into real-world electronic health records, with the guidance of domain experts. This benchmark enables a realistic assessment of the error detection capabilities of our system and provides a standardized testing ground for future research in this area.

Through extensive experiments, we conduct a thorough assessment of the effectiveness of our proposed approaches, demonstrating their performance through comprehensive evaluations and analyses. By comparing our system to state-of-the-art baselines and ablating various components of our framework, we aim to provide a clear understanding of the strengths and limitations of our approach, as well as identify potential avenues for future improvement.

In summary, our contributions are as follows:

- We propose a novel framework that employs a retrieval-augmented generation approach for clinical report error correction. This framework retrieves medical entities and relations both internally and externally to facilitate contextual and comprehensive reasoning.
- We introduce a three-stage approach for error detection and correction, which decomposes the task into distinct subtasks: error detection, error localization, and error correction. This decomposition not only serves as a benchmark but also enhances the explainability of the overall process.
- We establish a benchmark for the clinical report error detection task by intentionally introducing common mistakes into real-world electronic health records, with the guidance of domain experts. This benchmark enables a rigorous evaluation of error detection capabilities.

We conduct thorough experiments to assess the effectiveness of our proposed approaches, demonstrating their performance through comprehensive evaluations and analyses.

By harnessing the power of LLMs while addressing their limitations through a decomposed, multistage approach and reasoning mechanisms, our system aims to enhance the accuracy and reliability of clinical documentation, ultimately contributing to improved healthcare delivery and patient outcomes.

2 Related Work

2.1 Retrieval-Augmented Generation

Retrieval-augmented generation (RAG) is a technique that enhances the performance of LLMs by integrating an external knowledge retrieval component (Gao et al., 2023). The RAG architecture consists of two main modules: a retriever and a generator. The retriever is responsible for searching and ranking relevant information from a large-scale knowledge base, given an input query. The generator, usually a pre-trained LLM, takes the input query and the retrieved knowledge as context to generate the final output. RAG has shown promising results in various natural language processing tasks, such as question answering, fact verification, and dialogue systems (Chen et al., 2024; Jin et al., 2024).

Traditional RAG systems often rely on unstructured text retrieval from large-scale corpora, such as Wikipedia or domain-specific databases (Ke et al., 2024; Zhao et al., 2024). While this approach has shown success in various natural language processing tasks, it has limitations in retrieving valid information from massive free text compared to knowledge graph (KG) based retrieval (Wu et al., 2023). KGs often contain high-quality, curated knowledge that has been manually or semiautomatically extracted from reliable sources (Sanmartin, 2024). This curated knowledge tends to be more accurate and consistent compared to the potentially noisy and contradictory information found in unstructured text corpora (Jiang et al., 2024). The structured nature of KGs also enables easier integration of domain-specific knowledge, such as medical ontologies or scientific taxonomies, which can enhance the performance of RAG systems in specialized domains.

However, constructing and maintaining largescale, high-quality KGs can be challenging and resource-intensive. To address this issue, this work presents a simple yet efficient method for constructing KGs directly from the reference data used in RAG systems. By leveraging the information already available in the reference corpus, this approach eliminates the need for extensive manual curation or external knowledge sources. Furthermore, this method circumvents the requirement for additional fine-tuning of LLMs, which can be prohibitively expensive, especially in low-resource environments such as the medical domain (Thirunavukarasu et al., 2023; Sahoo et al., 2024).

2.2 RadGraph

RadGraph (Jain et al., 2021) is a tool for extracting clinical entities and relations from radiology reports. It introduces a carefully designed information extraction schema that aims to capture most clinically relevant information within a radiology report while enabling consistent and efficient annotation. The key aspects of RadGraph's entity and relation extraction approach are as follows: For entity extraction, RadGraph defines four entity types: Anatomy, Observation: Definitely Present, Observation: Uncertain, and Observation: Definitely Absent. Anatomy refers to anatomical body parts mentioned in the report, while observations encompass words associated with visual features, physiological processes, or diagnostic classifications. This novel entity typology facilitates comprehensive extraction of clinically salient information. Regarding relation extraction, RadGraph employs three relation types: suggestive_of, located_at, and modify. Suggestive_of captures inferred relationships between two observations. Located_at links an observation to an anatomy, indicating the anatomical location or context of the observation. Modify encodes modifier relationships, whereby one entity quantifies or scopes another entity of the same type. This principled relation schema enables Rad-Graph to represent complex semantic relationships within radiology reports. Our work mainly builds on RadGraph to extract entities and relations from radiology reports.

3 Method

Figure 1 illustrates the proposed work, which integrates internal and external retrieval, rephrasal augmentation, and finally with a three-stage inference process for step-by-step inference. The internal and external retrieval extracts relevant information

from the given note and reference corpus. Then the retrieved entities and relations are rephrased into sentences. The three-stage inference process then utilizes the retrieved information to detect, localize, and correct errors in the clinical note. By combining these components, the proposed system aims to improve the accuracy and quality of clinical reports.

3.1 Internal and External Retrieval

Internal Retrieval. Our work focuses on radiology report error correction which contains separate sections for Findings and Impression. The Findings section details observations from a radiograph, while the Impression section provides diagnostic conclusions drawn from those findings. Inspired by Yan et al. (2023), we transform this report into a graph representation using RadGraph. In the resulting graph, nodes correspond to two main types of entities: anatomical entities (e.g., lungs, ribs) and observational entities (e.g., clear, acute). Edges connecting these nodes denote relations such as modification (an observational entity modifying an anatomical entity), location (specifying the anatomical location of an observation), or suggestion (an observation suggesting a particular diagnosis).

The extraction of these key medical mentions and their relationships is expected to enable more targeted reasoning by the model, as it can focus on the most salient information while considering the connections between various entities. Moreover, RadGraph provides additional contextual information by categorizing observations based on their presence or absence in the report. Observations are denoted as either "Observation: Definitely Present" (OBS-DP) or "Observation: Definitely Absent" (OBS-DA). This explicit labeling of the presence or absence of observations enhances the input for the model, allowing it to better identify contextual inconsistencies within the report. By leveraging this rich graph-based representation of the clinical report, our method aims to improve the accuracy and consistency of the model's reasoning process.

External Retrieval. In addition to retrieving information from the given report, our method employs an external retrieval process to extract relevant entities and knowledge from a large-scale dataset of clinical reports, which we refer to as reference data. The purpose of this external retrieval is to provide supplementary knowledge and clinical

CLINICAL NOTE FINDINGS: PA and lateral views of the chest are provided. The previously seen left lower lobe opacity has disappeared. There is no acute cardiopulmonary process IMPRESSION: Enlarged pulmonary arteries. Step 1: Retrieve Step 2: Rephrase Internal Rephrasing Internal Retrieval No left lower lobe pneumonia. left lower acute cardiopulmonary ANAT-DP ANAT-DP ANAT-DP OBS-DP No acute cardiopulmonary process modify located at located at modify modify Enlarged pulmonary arteries. pulmonary arteries process pneumonia ANAT-DP ANAT-DP located at External Rephrasing EQ Left lower lobe is clear. No opacity in left lung base. **External Retrieval** Chest x-ray is unremarkable for acute cardiopulmonary findings. No radiographic evidence of acute cardiopulmonary process. RadGraph Increased pulmonary vascular Prominent main pulmonary artery Reference reports Step 3: Three-Stage Inference **Error Detection** Error Localization **Error Correction** Q: Does the report have error? Q: Where is the error? Q: Please correct the sentence. A: Yes A: Sentence No. 4 A: No acute cardiopulmonary process

Figure 1: An overview of our work. ANAT-DP: Anatomy-Definitely Present. OBS-DP: Observation-Definitely Present. OBS-DA: Observation-Definitely Absent.

findings from other reports that can aid in identifying errors or inconsistencies in the current report. By leveraging a broader context of medical information, our method aims to improve the accuracy and robustness of the error detection process.

To ensure consistency in data representation, we apply RadGraph to extract entities and relations from the reference data in the same manner as we do for the given report. The external retrieval process allows our method to access a vast repository of medical knowledge and real-world clinical findings. This can be particularly beneficial in cases where the given report may contain rare or complex medical conditions that require additional context for accurate interpretation. By drawing upon the collective knowledge present in the reference data, our method can make more informed decisions and potentially identify errors that might be difficult to

detect based solely on the information provided in the given report.

3.2 Rephrasal Augmentation

When applying RadGraph to extract entities and relations from radiology reports, we further rephrase the extracted information into concise sentences to enhance interpretability and downstream reasoning capabilities. RadGraph proposes a principled relation extraction schema to reconstruct radiology report findings from extracted clinical entities and their semantic relations. The schema defines three relation types: $suggestive_of$, $located_at$, and modify. These can be used to rephrase the entities and relations into sentences. For instance, consider a scenario where we have two relation triples: $\langle lower, modify, lobe \rangle$ and $\langle opacity, located_at, lobe \rangle$. The first triple indi-

cates that the entity "lower" modifies the entity "lobe," while the second triple signifies that the entity "opacity" is located at the entity "lobe." By combining these two triples based on their common entity "lobe," we can generate a meaningful phrase: "lower lobe opacity." This phrase captures the essential information conveyed by the individual relation triples, presenting it in a more concise and understandable manner. Furthermore, our method takes into account the negation of mentions, which is crucial for accurately representing the absence of certain findings. In cases where a mention is negated, we incorporate the word "no" at the beginning of the generated phrase. For example, if the relation triple $\langle opacity, located_at, lobe \rangle$ is negated, we would generate the phrase "no lobe opacity."

For a given report, our method retrieves the top k most similar reports from the reference data to provide additional context and support the error detection process. These retrieved reports serve as extra information in the input, augmenting the knowledge available to the model.

3.3 Three-Stage Inference

To enhance the inference capabilities and explainability of error correction in clinical reports, similar to Ben Abacha et al. (2024), we propose the three-stage approach by decomposing the task into three distinct subtasks: **error detection**, **error localization**, and **error correction**. By addressing these subtasks separately, the model can focus on smaller, more manageable objectives, leading to improved performance and increased interpretability.

In the error detection stage, the model aims to identify whether an error is present in the given clinical text. This binary classification task enables the model to distinguish between correct and incorrect information by learning the characteristics that indicate the presence of errors, such as inconsistencies, contradictions, or deviations from standard medical terminology. If an error is detected, the model proceeds to the error localization stage, where it pinpoints the precise location of the error within the text. This stage involves a fine-grained analysis of the clinical report, requiring the model to identify the specific words, phrases, or sentences that contain the error. By accurately determining the scope and nature of the error, the model can provide targeted corrections. In the final error correction stage, the model generates the corrected sentence based on the information gathered from

the previous stages. By leveraging the knowledge of the error's presence and location, the model can create a contextually appropriate correction that maintains the overall coherence and accuracy of the clinical report.

The three-stage approach offers several advantages over the end-to-end error correction task. By decomposing the task into smaller, focused subtasks, the model can learn more efficiently and effectively, capturing the intricacies of error detection and correction more accurately. This process allows the model to respond with higher accuracy by focusing on each subtask independently before combining the results. Furthermore, this approach helps to reduce hallucination by encouraging the model to think through the task step by step, mitigating the risk of generating irrelevant or inconsistent corrections. Moreover, the three-stage approach enhances the explainability of the model. By separating the error detection, localization, and correction processes, it becomes easier to interpret the model's decisions and understand the reasoning behind its predictions. Each stage provides clear insights into the model's thought process, from identifying the presence of an error to pinpointing its location and generating a suitable correction.

4 Experiment

4.1 Dataset

Our study utilizes chest radiology reports from the MIMIC-CXR dataset (Johnson et al., 2019) as an exemplar. MIMIC-CXR is a large-scale collection of real-world radiology data, providing a valuable resource for our analysis. From this dataset, we employ 112,251 radiology reports as reference data, representing correctly annotated ground truth reports. Additionally, we curate 1,622 reports as evaluation data, where a subset of these reports are purposefully corrupted to simulate real-world annotation errors (see details in Table 1).

Reference data will be used for external retrieval to provide augmented knowledge and clinical findings for error detection and correction. Evaluation data, on the other hand, refers to the data used for evaluation of the task, where some of the reports contain errors.

To introduce realistic errors into the evaluation data, we employ two strategies with the guidance of clinical experts and radiologists. Firstly, we replace essential clinical observations with irrelevant ones. Specifically, we utilize the 12 important ob-

	Correct	Incorrect		Total
		FIND	IMPN	•
Reference Data	112,251	-	-	112,251
Evaluation Data	512	582	528	1,622

Table 1: Data used in this work. FIND: Findings (# of reports that have errors in the Findings). IMPN: Impression (# of reports that have errors in the Impression). Each report can only have at most one error (either it is from Findings or Impression).

servations from the CheXpert dataset (Irvin et al., 2019) (excluding "No Finding" and "Support Devices" from the original 14 observations) and substitute them with unrelated observations carefully selected to be clinically irrelevant to the report context. Secondly, we selectively alter the polarity of observations by removing negation words such as "no" or "no evidence of", effectively transforming negated findings into affirmed ones. This process aims to mimic common annotation mistakes where the presence or absence of clinical findings is incorrectly recorded. By corrupting a subset of the evaluation data through these two strategies, we aim to create a more challenging and realistic benchmark that captures the types of errors that may arise in practical radiology report annotation scenarios.

4.2 Evaluation

We report performance on the three-stage inference process, which includes error detection, localization, and correction. We calculate the accuracy for error detection and localizaiton. To evaluate the performance of the generative error correction stage, we use an aggregate Natural Language Generation (NLG) score, namely AggNLG, that combines ROUGE-1 (Lin, 2004), BERTScore (Zhang et al., 2019), and BLEURT (Sellam et al., 2020). This aggregate score has been shown to align best with human judgement compared to other NLG metrics, providing a comprehensive assessment of the quality and semantic similarity between the generated corrections and the ground truth (Abacha et al., 2023b).

4.3 Baseline

For comparison, we select various state-of-the-art LLMs from both the general and medical domains to benchmark our proposed approach. In the general domain, we choose the latest LLMs, which are LLaMA3 and Phi3, as our base models(Abdin et al., 2024). These models have demonstrated strong performance across a wide range of natu-

ral language processing tasks. For LLaMA3, we utilize the 8B parameter version (LLaMA3-8B¹) due to computational resource limitations, opting out of the larger 70B model. For Phi3, we compare different model sizes, including Phi3-mini-3.8B², Phi3-small-7B³, and Phi3-medium-14B⁴, to investigate the impact of model scale on the performance. Furthermore, to explore the potential benefits of domain-specific knowledge, we consider two medical LLaMA3-8B variants, Llama3-Aloe-8B-Alpha⁵ and MMedLM2⁶(Qiu et al., 2024; Gururajan et al., 2024). These models built on LLaMA3-8B, and have been further fine-tuned on a wide range of medical instructional datasets, synthetic medical data, medical textbooks, medical websites, etc.

5 Result

5.1 Comparisons with Three-Stage Inference

Table 2 presents a comparison of the performance of various language models on the tasks of error detection, localization, and correction using three-stage inference and end-to-end approaches. For the three-stage inference approach, the accuracy scores for error detection range from 37.79% (Llama3-8B) to 79.03% (Phi3-small). Error localization accuracy follows a similar trend, with Llama3-8B achieving the lowest score (37.29%) and Phi3-medium obtaining the highest (69.73%). In terms of error correction, the aggregate NLG score (AggNLG) is used to assess performance, where AggNLG is the averagte score of ROUGE-1, BERTScore, and BLEURT. Llama3-8B achieves the highest AggNLG score of 94.29%, followed closely by Phi3-medium and Aloe. The end-to-end error correction approach, yields similar pattern compared with the three-stage inference approach, where Llama3-8B and Phi3-medium achieves the top two AggNLG scores.

Comparing the three-stage inference and endto-end approaches, it is evident that the threestage inference generally yields higher AggNLG scores for error correction. The two medical LLMs,

¹https://huggingface.co/meta-llama/Meta-Llama-3-8B-Instruct

²https://huggingface.co/microsoft/Phi-3-mini-4k-instruct ³https://huggingface.co/microsoft/Phi-3-small-8k-instruct

⁴https://huggingface.co/microsoft/Phi-3-medium-4k-instruct

⁵https://huggingface.co/HPAI-BSC/Llama3-Aloe-8B-Alpha

⁶https://huggingface.co/Henrychur/MMedLM2

		End-to-End		
	Error Detection	Error Localization	Error Correction	Error Correction
	ACC	ACC	AggNLG	AggNLG
MMedLM2	41.49	30.94	58.27 (+10.47)	47.80
Aloe	45.31	43.34	90.17 (+26.84)	63.33
Phi3-mini	67.26	47.71	74.08 (-0.28)	74.36
Phi3-small	79.03	63.44	86.57 (+6.53)	80.03
Phi3-medium	73.67	69.73	90.25 (+5.79)	84.47
Llama3-8B	37.79	37.29	94.29 (+9.95)	84.34

Table 2: Comparisons with three-stage inference and end-to-end inference of error correction. AggNLG is the averagte score of ROUGE-1, BERTScore, and BLEURT.

	Baseline	Internal	Internal + Ex
MMedLM2	41.49	39.33	73.05 (+31.56)
Aloe	45.31	35.14	67.26 (+21.95)
Phi3-mini	67.26	69.66	73.06 (+5.80)
Phi3-small	79.03	78.48	80.21 (+1.18)
Phi3-medium	73.67	68.93	79.04 (+5.37)
Llama3-8B	37.79	37.92	62.27 (+24.48)

Table 3: Comparisons of internal and external retrieval on error detection (accuracy).

MMedLM2 and Aloe, improves the most with 10.47% and 26.84% respectively. Phi3-mini does not show improvements in this case, with a slight decrease of 0.28%. The overall performance suggests that breaking down the error correction process into distinct stages of detection, localization, and correction can lead to better overall performance compared to an end-to-end approach.

Another point worth noticing is that the calculation of error correction requires the model to analyze the input radiological report: if an error is detected, the model will correct it by generating the amended report entirety; otherwise, it will return "NA". The scoring process is conducted exclusively when both the model and the ground truth identify errors (neither being "NA"), and the rectified results are compared. Radiological report errors typically involve minor corrections of a few words, leaving the majority of the report content unaltered, which explains the generally higher NLG scores in the result Tables.

5.2 Comparisons with Internal and External Retrieval

Table 3-5 present comparisons of internal and external retrieval methods on error detection (Table 3), error localization (Table 4), and error correction (Table 5).

In Table 3, which focuses on error detection ac-

	Baseline	Internal	Internal + Ex
MMedLM2	30.94	29.28	46.05 (+15.11)
Aloe	43.34	34.83	51.35 (+8.01)
Phi3-mini	47.71	39.95	52.65 (+4.94)
Phi3-small	63.44	65.22	65.04 (+1.60)
Phi3-medium	69.73	65.65	63.44 (-6.29)
Llama3-8B	37.29	36.99	53.14 (+15.85)

Table 4: Comparisons of internal and external retrieval on error localization (accuracy).

	Baseline	Internal	Internal + Ex
MMedLM2	58.27	52.66	53.50 (-4.77)
Aloe	90.17	89.81	74.77 (-15.40)
Phi3-mini	74.08	76.78	78.85 (+4.77)
Phi3-small	86.57	89.09	86.67 (+0.10)
Phi3-medium	90.25	92.41	92.25 (+2.00)
Llama3-8B	94.29	94.49	94.43 (+0.14)

Table 5: Comparisons of internal and external retrieval on error correction (AggNLG).

curacy, where all models significantly improves while applying both internal and external retrieval. MMedLM2 improves the most by 31.56% and Phi3-small improves the least by 1.18%. Additionally, it is observed that using only internal retrieval does not improve the performance significantly. Only Phi3-mini and Llama3-8B shows improvement with internal retrieval.

Table 4 presents results for error localization accuracy. All models show improvement while using both internal and external retrieval, except for Phi3-medium. Llama3-8B and MMedLM2 improve the most by more than 15%. Similar to error detection, it is noticed that internal retrieval does not provide effectiveness for this task as well, where only Phi3-small shows increased accuracy with internal retrieval.

Table 5 shows the error correction results. The combination of internal and external retrieval further enhances the error correction performance for most models, though the two medical LLMs do not

benefit from the retrieval. Phi3-mini achieves the highest relative improvement by 4.77%. Similarly, Phi3-small and Phi3-medium and Llama3-8B benefit from the addition of external retrieval, with their AggNLG scores rising to 86.67% and 92.25%, and 94.43% respectively. These results suggest that the effectiveness of external retrieval in enhancing error correction performance varies across different language models. General domain models, such as Phi3 and Llama3 benefit significantly from the combination of internal and external retrieval, however, medical LLMs (MMedLM2 and Aloe), may not experience substantial gains or even exhibit a slight performance decline. This indicates medical LLMs may need different retrieval strategies.

Overall, these tables demonstrate the effectiveness of internal and external retrieval methods in enhancing the performance of language models on error detection, localization, and correction tasks. The results suggest that incorporating retrieval mechanisms can lead to significant improvements in accuracy and AggNLG scores compared to the baseline models.

6 Discussion

The results presented in this study demonstrate the effectiveness of the internal and external retrieval method in enhancing the performance of language models on error detection, localization, and correction tasks. Across all three tasks, our proposed approach consistently improves upon the baseline and internal retrieval methods for most of the models tested.

One notable observation while looking into detail with the models' predictions is the varying performance of the models based on their underlying architectures and training data. The Llama3-8B model exhibits a strong ability to follow instructions, performing well when provided with clear and detailed prompts. However, its performance may suffer when given ambiguous instructions. In contrast, the Phi3 models demonstrate extensive knowledge and perform well even with vague instructions. However, when the instructions conflict with their internal understanding or knowledge, their performance tends to decline. Additionally, the Phi3 models are less adept at following instructions compared to Llama3-8B, occasionally deviating from the required output format or generating excessive content.

The two medical-specific models, MMedLM2

and Aloe, benefits the most with error detection but the least with error correction. It is noticeable that MMedLM2 performs the worst among all models. When provided with relevant information through the retrieval approach, Aloe demonstrates improved performance, while MMedLM2 continues to generate excessive and repetitive content. This suggests that fine-tuning may have impacted the language capabilities of the base Llama3 model. Overall, the fine-tuned models do not perform as well as the general-purpose Llama3 model.

In conclusion, the combined retrieval method proves to be a valuable approach for enhancing the performance of language models on error detection, localization, and correction tasks. However, the effectiveness of this method varies depending on the underlying model architecture, training data, and the clarity of instructions provided. While the Llama3-8B model excels at following instructions, the Phi3 models demonstrate strong performance in zero-shot scenarios. Fine-tuning models on domain-specific data, such as medical text, may impact their language capabilities, and careful consideration should be given to the training data and prompts used during the fine-tuning process. Future research should explore methods to improve the models' understanding and utilization of summary information, as well as investigate strategies to balance the benefits of domain-specific finetuning with the preservation of general language capabilities.

7 Conclusion

In conclusion, this study introduces a novel framework for error detection, localization, and correction in clinical radiology reports, combining the strengths of LLMs and RAG techniques. The proposed approach leverages internal and external retrieval mechanisms to extract relevant medical entities and relations, enhancing the contextual understanding of the LLMs. By decomposing the task into three distinct subtasks through a three-stage inference process, the system achieves improved performance and explainability compared to end-toend approaches. Experimental results on a benchmark dataset, created by corrupting real-world radiology reports with realistic errors, demonstrate the effectiveness of the proposed methods. The combination of internal and external retrieval significantly improves the accuracy of error detection, localization, and correction across various state-ofthe-art LLMs.

Limitation

While our current study focuses on radiology reports, we recognize the potential for extending our method to a broader range of clinical notes. In future work, we plan to expand the scope of our research by exploring the application of RadGraph to a wider variety of medical entities, going beyond radiographic studies. By incorporating entities and relations from diverse types of clinical notes, such as progress notes, discharge summaries, and consultation reports, we aim to generalize our error correction method to a more comprehensive set of medical documents.

The study also highlights the varying performance of LLMs based on their underlying architectures, training data, and instruction clarity. While general-purpose LLMs like Llama3-8B and Phi3 benefit from the proposed approach, domain-specific models, such as MMedLM2 and Aloe, exhibit limitations that warrant further investigation. It is suggested different retrieval strategies should be tailored for medical LLMs.

Furthermore, to obtain a more robust assessment of the error correction performance, enhanced evaluation methods are also should be considered in the future. One promising avenue is to incorporate human evaluations from domain experts, such as radiologists and other clinicians. These expert assessments would provide invaluable insights into the clinical relevance and accuracy of the generated corrections, complementing the automated evaluation metrics used in this study.

Ethics Statement

This work uses the de-identified clinical notes in MIMIC-CXR. We complete the Collaborative Institutional Training Initiative (CITI) Program's "Data or Specimens Only Research" course⁷ and sign the data use agreement to get access to the data. We strictly follow the guidelines and only use locally hosted LLMs with the data.

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A Appendix

Experiment Setups. All the experiments are conducted with 4 NVIDIA GeForce RTX 3090. For our LLM experiments, we utilize the AutoModelForCausalLM from the Hugging Face Transformers library. The model is loaded from the specified model_id, with the torch_dtype parameter set to torch.bfloat16. We set the max_new_tokens=300, do_sample=True, temperature=0.001 and top_p=0.8, all other hyperparameters remains unchanged as default values.

RAG pipeline. We use the e5-large-unsupervised model (Wang et al., 2022) to transform internal and external datasets into a vectorized database. This process involves applying cosine similarity to find the most similar texts based on the input radiology reports. The experiment uses parameters set to chunk_size=1000 and chunk_overlap=100.

Evaluation Data Preparation. The list of 12 observations we choose to replace: 'Atelectasis', 'Cardiomegaly', 'Consolidation', 'Edema', 'Enlarged Cardiomediastinum', 'Fracture', 'Lung Lesion', 'Lung Opacity', 'Pleural Effusion', 'Pleural Other', 'Pneumonia', 'Pneumothorax'. The replacement words

'Asthma', 'Costochondritis', 'Pulmonary Embolism', 'Thoracic Outlet Syndrome', 'Tracheitis', 'Tracheomalacia', 'Vocal Cord Dysfunction', 'Pharyngitis','Laryngitis','Mesothelioma','Obstructive Sleep Apnea', 'Aspergillosis'; 'Appendicitis', 'Gastroesophageal Reflux Disease', 'Crohns Disease', 'Ulcerative Colitis', 'Gallstones', 'Pancreatitis', 'Hepatitis', 'Cirrhosis', 'Irritable Bowel Syndrome', 'Peptic Ulcer', 'Celiac Disease', 'Diverticulitis', 'Hemorrhoids', 'Anal Fissure', 'Intestinal Obstruction', 'Inflammatory Bowel Disease', 'Gastroparesis', 'Cholecystitis', 'Gastric Ulcer', 'Duodenal Ulcer', 'Esophageal Varices', 'Achalasia', 'Barretts Esophagus', 'Esophageal Cancer', 'Pancreatic Cancer', 'Colorectal Cancer', 'Liver Cancer', 'Gastric Cancer', 'Hiatal Hernia', 'Esophageal Stricture'.

	Reference Data		Evaluation Data	
	Findings (%)	Impression(%)	Findings(%)	Impression(%)
ANAT-DP	1,261,293 (46)	306,632 (37)	21,090 (46)	5,475 (42)
OBS-DP	1,002,276 (37)	319,179 (39)	18,726 (41)	6,215 (48)
OBS-U	81,331 (3)	65,491 (8)	1,559 (3)	1,231 (9)
OBS-DA	371,429 (14)	135,573 (16)	4,859 (11)	136 (1)
Total Entities	2,716,329 (100)	826,875 (100)	46,234 (100)	13,057 (100)
Modify	1,124,901 (59)	333,435 (60)	20,568 (62)	5,754 (61)
Located_at	712,778 (38)	182,083 (33)	11,373 (34)	2,913 (31)
Suggestive_of	62,372 (3)	39,120 (7)	1,213 (4)	700 (7)
Total Relations	1,900,051 (100)	554,638 (100)	33,154 (100)	9,367 (100)

Table 6: Data Statistics. ANAT-DP: Anatomy-Definitely Present. OBS-DP: Observation-Definitely Present. OBS-U: Observation-Uncertain. OBS-DA: Observation-Definitely Absent.

End-to-End Prompt

Task Description::

You are a professional radiologist responsible for understanding chest radiology and writing diagnostic reports. Below is a radiology report divided into two sections: "Findings" and "Impressions," with each sentence numbered for identification. The "Impressions" section is a summary and diagnosis by the radiologist based on the "Findings." You need to check this report for any medical errors. There may be one medical error or none in the report.

Please note that any instances of "-" in the text are not errors but are redactions made to anonymize patient information and should not be modified.

Respond appropriately: If you identify a medical error within the report, directly amend the error sentence in the input text. Output corrected full report text. Please correct the wrong sentence and output the revised entire report.

If no errors are detected after your review, 'NA'. Output the full original input report.

Input report: [...]
Output Format:

Corrected full report: (string)

Three-Stage Inference Prompt

Task Description::

You are a professional radiologist responsible for understanding chest radiology and writing diagnostic reports. Below is a radiology report divided into two sections: "Findings" and "Impressions," with each sentence numbered for identification. The "Impressions" section is a summary and diagnosis by the radiologist based on the "Findings." You need to check this report for any medical errors. There may be one medical error or none in the report.

Please note that any instances of "." in the text are not errors but are redactions made to anonymize patient information and should not be modified.

Respond appropriately: Lets think step by step. If you find a medical error, you need to: Set the error flag to 1. Provide the ID of the error sentence. And then generate the corrected full report text. Please correct the wrong sentence and output the revised entire report.

If no error is found: Set the error flag to 0. Set the erroneous sentence ID to -1. And output the correct full report as 'NA'.

Input report: [...]
Output format:
Error Flag:\(\lambda\) (number\)
Error Sentence ID:\(\lambda\) (string\)
Corrected full report: \(\lambda\) (string\)

Figure 2: Prompt used for end-to-end and three-stage inference.

Internal Retrieval Prompt

Task Description::

You are a professional radiologist responsible for understanding chest radiology and writing diagnostic reports. Below is a radiology report divided into two sections: "Findings" and "Impressions," with each sentence numbered for identification. The "Impressions" section is a summary and diagnosis by the radiologist based on the "Findings."

There is a medical error in the sentence (number). Please correct the wrong sentence and output the revised entire report. Please note that any instances of "..." in the text are not errors but are redactions made to anonymize patient information and should not be modified.

To help you understand the input text, I have provided a summary text for your reference.

summary text: [...]

Respond appropriately: Lets think step by step. If you find a medical error, you need to: Set the error flag to 1. Provide the ID of the error sentence. And then generate the corrected full report text. Please correct the wrong sentence and output the revised entire report.

If no error is found: Set the error flag to 0. Set the erroneous sentence ID to -1. And output the correct full report as 'NA'.

Input report: [...]
Output format:
Error Flag:\(\lambda\) unmber\\
Error Sentence ID:\(\lambda\) umber\\
Corrected full report: \(\lambda\) string\\

External Retrieval Prompt

${\bf Task\ Description::}$

You are a professional radiologist responsible for understanding chest radiology and writing diagnostic reports. Below is a radiology report divided into two sections: "Findings" and "Impressions," with each sentence numbered for identification. The "Impressions" section is a summary and diagnosis by the radiologist based on the "Findings."

There is a medical error in the sentence (number). Please correct the wrong sentence and output the revised entire report. Please note that any instances of "..." in the text are not errors but are redactions made to anonymize patient information and should not be modified.

Reference Material: Below are some example radiology reports similar to the input text. All these reports are correct and must be used for reference.

Example 1: [...

Example 2: [...

Example 3: [...

Example 4: [...]

Respond appropriately: Lets think step by step. If you find a medical error, you need to: Set the error flag to 1. Provide the ID of the error sentence. And then generate the corrected full report text. Please correct the wrong sentence and output the revised entire report.

If no error is found: Set the error flag to 0. Set the erroneous sentence ID to -1. And output the correct full report as 'NA'.

Input report: [...]

Output format: Error Flag:\(\lambda\) number\(\rangle\)

Error Flag:\(\number\)
Error Sentence ID:\(\number\)

Corrected full report: (string)

Figure 3: Prompt used for internal and external retrieval.