**EXL Services- Health care at MEDIQA-WV 2025: A Multi-Stage Pipeline with Metadata Prediction and Prompt Mining for Wound Care Visual Question Answering**

Abstract:

The rapid expansion of asynchronous remote care has intensified provider workload, creating demand for AI systems that can assist clinicians in managing patient queries more efficiently. The **MEDIQA-WV 2025 shared task** addresses this challenge by focusing on generating free-text responses to wound care queries paired with images. In this work, we present two complementary approaches developed for the English track. The first leverages a **mined prompting strategy**, where training data is embedded and the top-k most similar examples are retrieved to serve as few-shot demonstrations during generation. The second approach builds on a **metadata ablation study**, which identified four metadata attributes that consistently enhance response quality. We train classifiers to predict these attributes for test cases and incorporate them into the generation pipeline, dynamically adjusting outputs based on prediction confidence. Experimental results demonstrate that mined prompting improves response relevance, while metadata-guided generation further refines clinical precision. Together, these methods highlight promising directions for developing AI-driven tools that can provide reliable and efficient wound care support.

**Introduction:**  
  
The proliferation of remote patient care, accelerated by telehealth technologies, has transformed how patients and providers interact. Patients can now communicate asynchronously through secure portals, often submitting free-text messages and images for clinical review. While this model greatly improves accessibility and continuity of care, it has also generated new challenges for healthcare systems. Providers face an ever-growing volume of digital queries, creating what has been termed the “inbox burden” (Sinsky et al., 2024). This constant stream of patient messages can delay response times, reduce clinical efficiency, and contribute to physician burnout.

Artificial intelligence (AI)–based natural language generation offers a promising strategy to alleviate this workload. By producing high-quality draft responses to patient messages, such systems can streamline communication workflows, reduce repetitive documentation tasks, and allow clinicians to devote more time to complex decision-making. Previous work has shown that retrieval-augmented generation (RAG) methods (Lewis et al., 2020; Gao et al., 2023) and clinical domain adaptation of large language models (LLMs) (Singhal et al., 2023; Lehman et al., 2023) can substantially improve the quality and reliability of AI-generated text in medical settings. However, applying these models in specialized areas such as wound care remains relatively unexplored.

Wound care presents unique challenges for automated response generation. Accurate assessment often depends on both **visual attributes** (e.g., wound type, tissue appearance, exudate characteristics) and **textual context** (e.g., patient-reported symptoms, history of treatment). This multimodal nature requires systems that can integrate visual and textual signals to produce clinically appropriate outputs. The **MEDIQA-WV 2025 shared task** (Yim et al., 2025a) directly addresses this gap by providing a benchmark for generating free-text responses to patient wound care queries that include both text and images. The task advances prior MEDIQA challenges (Ben Abacha et al., 2021; Yim et al., 2023) by focusing on asynchronous, visually grounded care scenarios, thereby moving closer to real-world clinical applications.

In this paper, we present the work, developed for the English track of MEDIQA-WV 2025. Our central hypothesis is that generic, end-to-end vision-language models may lack the domain-specific grounding required for wound care queries. To address this, we investigate two complementary approaches: (1) a mined few shot prompting strategy, where the system retrieves clinically similar examples from the training data to guide generation, and (2) a metadata-guided generation strategy, where structured wound attributes predicted by classifiers are incorporated into the generation process. Our contributions are as follows:

1. We evaluate **mined few-shot prompting** and **metadata-guided response generation**, highlighting their complementary strengths for clinical text generation.
2. We provide empirical evidence that structured context—retrieved or predicted—significantly improves the quality of wound care response generation in English patient queries.

**2. Shared task and Dataset**

The MEDIQA-WV 2025 shared task focuses on wound care visual question answering (VQA), where the goal is to generate clinically coherent responses to patient queries about wounds by leveraging both wound images and textual inputs. The task is built on the recently introduced WoundcareVQA dataset (Yim et al., 2025b), which consists of approximately 500 multilingual patient queries (English and Chinese). Each query is paired with one or two wound images and multiple expert-authored responses, enabling a multimodal setup that requires both visual and linguistic reasoning.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Split** | **Cases** | **Images** | **Responses** | **Responses per Case** | **Avg. Query Length** | **Avg. Response Length** |
| Training | 279 | 449 | 279 | 1 | 44 words | 29 words |
| Validation | 105 | 147 | 210 | 2 | 47 words | 36 words |
| Test | 93 | 152 | 279 | 3 | 52 words | 47 words |
| **Total** | 477 | 748 | 768 | – | – | – |

In addition to raw queries and expert responses, each case is annotated with structured metadata covering clinically relevant wound attributes. These attributes serve as a rich source of metadata, covering aspects such as:

* **Anatomic Location** (e.g., *lower leg, abdomen, fingernail*)
* **Wound Type** (e.g., *surgical, traumatic, pressure ulcer*)
* **Wound Thickness** (e.g., *superficial, full thickness*)
* **Tissue Color** (e.g., *pink, red and moist, black*)
* **Drainage Type and Amount**
* **Signs of Infection**

An important characteristic of this dataset is the variability in inter-annotator agreement (IAA) across wound attributes. For example, wound type (1.0), tissue color (0.97), and infection (0.97) achieved near-perfect agreement, suggesting these features are well-defined and consistently identified by clinicians. In contrast, anatomic location (0.81), drainage amount (0.86), and wound thickness (0.89) show relatively lower agreement, highlighting attributes that are either more subjective or context-dependent. These differences emphasize that while certain wound features provide highly reliable signals for model training and evaluation, others introduce ambiguity that must be accounted for in system design and assessment.

This combination of free-text responses and structured wound attributes makes the dataset uniquely suited for hybrid approaches that combine classification and generation, and provides an opportunity to evaluate how multimodal systems handle both objective and subjective aspects of wound care reasoning.

**3. Related work**

In recent years, multimodal machine learning has gained considerable traction in healthcare applications, particularly with the rise of large multimodal models. Several open-source initiatives have pushed this field forward, including **LLaVA-Med** (Li et al., 2023) and **ELIXR** (Xu et al., 2023). The latter is especially notable for exploring CLIP-inspired training strategies, which closely align with the objectives of our work. Much of the current research has centered on radiology and other imaging-heavy specialties, while dermatology has received relatively limited attention. Notable early studies, such as Cirone et al. (2024), demonstrated that GPT-4V can distinguish melanoma from benign skin lesions with high reliability. However, this type of binary diagnostic task is substantially more constrained than the open-ended dermatology question answering examined in the present shared task, where queries and conditions may extend beyond the model’s training distribution. The difficulty of this broader problem is evident in our findings: although our system achieved only moderate overall accuracy, it nonetheless ranked first in the competition. This outcome underscores both the progress achieved and the significant challenges that remain in developing robust multimodal systems for dermatology. These results point to several important directions for future research, including evaluation frameworks that better reflect clinical utility (Kelly et al., 2019) and methods to enhance multimodal reasoning beyond narrow diagnostic endpoints.

Our methodology builds on two key ideas. First, structured attribute prediction is a well-established strategy in computer vision for grounding model decisions in interpretable features (Russakovsky et al., 2015; Zhang et al., 2023). Second, our **prompt mining strategy** draws from retrieval-augmented generation (RAG) and in-context learning, where supplementing prompts with carefully selected examples has been shown to markedly improve large language model performance on domain-specific tasks (Lewis et al., 2020; Gao et al., 2023; Khandelwal et al., 2020).

**4. Methodology**

Our system is a pipeline designed to maximize the use of both structured and unstructured information available in the dataset. It leverages two powerful models and is orchestrated through two distinct approaches.

**4.1. Model Description**

**MedGemma (27B):**MedGemma (27B Multimodal), from Google’s Gemma 3 family, is a large language model specialized for medical contexts. Crucially, its multimodal variants integrate MedSigLIP—a 400-million parameter dual-tower vision–language encoder (SigLIP-based), pre-trained on diverse medical imaging data (e.g., dermatology, radiology, pathology. MedSigLIP powers the visual understanding in MedGemma, allowing the model to reason across modalities. While we treat MedGemma separately from InternVL, its built-in image encoder makes it a strong alternative for end-to-end medical image understanding and free-text clinical response generation, particularly when vision and language reasoning need seamless integration.

**InternVL 3 (38B):** InternVL-3 38B is an advanced multimodal large language model (MLLM) that demonstrates superior multimodal perception and reasoning capabilities compared to its predecessor InternVL 2.5The architecture follows the "ViT-MLP-LLM" paradigm with pixel unshuffle operations that reduce visual tokens to one-quarter of the original. The model extends multimodal capabilities to encompass tool usage, GUI agents, industrial image analysis, and 3D vision perception. InternVL3-38B achieves competitive performance with leading models like GPT-4o on multimodal benchmarks, making it particularly suitable for complex visual-linguistic tasks such as medical image analysis and wound care assessment applications requiring precise visual-textual integration.

**4.2. Approach 1: Metadata ablation study and conditional metadata prediction for response generation**

The goal of this study was to identify which clinical features had the most significant impact on response quality and to develop a strategy for leveraging them effectively.

First, we systematically evaluated the importance of each of the seven metadata categories provided in the dataset. By removing one category at a time from a full-context prompt and measuring the resulting drop in the deltaBLEU score, we quantified the contribution of each feature. This empirical analysis, combined with an examination of the dataset's inter-annotator agreement (IAA) scores,This score is a heuristic derived directly from the **relaxed inter-annotator agreement scores** provided with the dataset, which serves as a proxy for the reliability of a given category.

Based on these findings, we designed a two-stage pipeline centered on high-impact features:

1. **Metadata Prediction:** For each instance in the test set, we use **MedGemma (27B)** to predict values for the four selected metadata categories. The task is framed as a few-shot classification problem where the model is prompted to select the most appropriate label from the predefined list based on the patient's query and a description of the images.
2. **Confidence Score Assignment and Conditional Integration:** To account for the inherent ambiguity in clinical assessment, we assign a "confidence score" to each predicted metadata field. In the second stage of our pipeline, this predicted metadata and its confidence score are passed as context alongside the original query and images. We use a confidence threshold of **0.7** to determine how this information shapes the final response. If a metadata field's confidence is **≥ 0.7**, its predicted value is integrated into the prompt as a factual observation. If the confidence is lower, the prompt instructs the model to be cautious about that aspect, preventing overconfident and potentially incorrect advice.

**4.3 Approach 2: Prompt Mining**In this approach, we leverage a dynamic few-shot prompting strategy to generate clinically grounded responses. First, the training dataset is embedded using the *all-mpnet-base-v2* sentence transformer, enabling efficient semantic similarity search. For each test query, the most relevant examples are retrieved from the training set and incorporated into the prompt. Specifically, we employ the InternVL3-38B model with the top 25 retrieved samples and the MedGemma-27B model with the top 5 retrieved samples, allowing each model to benefit from context sizes suited to its architecture. The enriched prompts, containing both the patient’s query and carefully selected training examples, guide the models to produce accurate, coherent, and clinically appropriate responses.

**5. Evaluation Metrics**

System performance was evaluated using the official metrics of the shared task, which are designed for multi-reference free-text generation:

**deltaBLEU:** A variant of SacreBLEU developed for response generation, a case in which many diverse gold standard responses are possible (Galley et al., 2015). The metric incorporates humanannotated quality rating and assigns higher weights to n-grams from responses rated to be of higher quality. The authors have shown this method produces higher correlation with human rankings compared to previous BLEU metrics. In our system, we assign response weights according to four criteria: (a) if user expertise level is 4 or above (out of 9), (b) if user is formally validated as a medical doctor by the platform, (c) if the response answer is the most frequent answer, and (d) if the response answers the query completely. The former two were manually assigned to the validation and test sets by two NLP scientists. The test set was double-reviewed. Out of a 0.0-1.0 scale, if (d) is not met, the score is discounted to 0.9; for the other 3 criteria, 0.1 is discounted for every missing element to reach the final weight.

**BERTScore:** An embedding-based metric that measures the semantic similarity between the generated and reference texts.

**ROUGE-L:** A recall-oriented metric that measures the longest common subsequence.

**6. Results and Discussions**

**Results and Discussion**

**4.1 Performance Comparison**

Table 1 presents the performance comparison across three methodological approaches using key evaluation metrics.

**Table 1: Performance Comparison Across Approaches**

| **Approach** | **deltaBLEU** | **ROUGE-L** | **DeepSeekV3** | **Gemini** | **GPT-4o** | **Average Human Eval** |
| --- | --- | --- | --- | --- | --- | --- |
| Metadata Ablation Study | 5.70 | 0.456 | 0.607 | 0.629 | 0.667 | 0.634 |
| MedGemma-27B (5-shot) | 13.04 | 0.452 | 0.591 | 0.629 | 0.616 | 0.612 |
| InternVL3-38B (25-shot) | 9.92 | 0.456 | 0.645 | 0.715 | 0.473 | 0.611 |

**4.2 Metadata Ablation Study Analysis**

To identify the most clinically relevant features for wound assessment, we conducted a systematic ablation study examining the contribution of each metadata category. Table 2 demonstrates the impact of removing individual metadata components on model performance.

**Table 2: Metadata Ablation Study Results (deltaBLEU)**

|  |  |  |
| --- | --- | --- |
| **System Configuration** | **deltaBLEU** | **Performance Drop** |
| All metadata classes | 4.476 | - |
| Without metadata | 3.786 | -0.690 |
| Without infection | 4.384 | -0.092 |
| Without drainage type | 4.254 | -0.222 |
| Without drainage amount | 4.962 | +0.486 |
| Without tissue color | 4.021 | -0.455 |
| Without wound thickness | 4.976 | +0.500 |
| Without wound type | 4.014 | -0.462 |
| Without anatomical location | 3.960 | -0.516 |
|  |  |  |

The ablation results reveal that **anatomical location** (-0.516), **wound type** (-0.462), and **tissue color** (-0.455) cause the most significant performance degradation when removed, indicating their critical importance for accurate wound assessment. Conversely, removing **wound thickness** (+0.500) and **drainage amount** (+0.486) actually improved performance, suggesting these features may introduce noise or ambiguity in the current dataset context.

**6.3 Inter-Annotator Agreement and Feature Selection**

The dataset exhibits considerable variability in inter-annotator agreement (IAA) across wound attributes, which directly correlates with their clinical utility. **Wound type** (1.0), **tissue color** (0.97), and **infection** (0.97) achieved near-perfect agreement, indicating these features are well-defined and consistently identified by clinicians. In contrast, **anatomical location** (0.81), **drainage amount** (0.86), and **wound thickness** (0.89) demonstrated lower agreement, highlighting attributes that are more subjective or context-dependent.

Based on the combined analysis of ablation study results and IAA scores, we selected **anatomical location**, **wound type**, **drainage type**, and **tissue color** as the most important metadata features for test data prediction. This selection strategy prioritizes features that either demonstrate high clinical impact (anatomical location, wound type, tissue color) or maintain reasonable reliability despite moderate IAA scores (drainage type: 0.92 IAA).

**6.4 Comparative Analysis and Clinical Implications**

**MedGemma-27B with few-shot prompting** achieved the highest deltaBLEU score (13.04), representing a 131% improvement over the metadata ablation approach (5.70). This superior performance can be attributed to the model's domain-specific medical training and optimal utilization of contextual examples. The consistency across human evaluation metrics (0.591-0.629) further validates this approach's clinical relevance.

**InternVL3-38B** demonstrated intermediate performance (deltaBLEU: 9.92) despite utilizing a larger context window with 25 retrieved samples. While the multimodal architecture shows promise, its general-purpose training may limit effectiveness in specialized clinical domains requiring precise medical terminology and wound-specific knowledge.

The **metadata ablation study** approach, while providing valuable insights into feature importance, achieved the lowest deltaBLEU score (5.70). This suggests that the two-stage pipeline may suffer from error propagation during metadata prediction, and the confidence threshold mechanism (0.7) may have been overly conservative in integrating predicted clinical features.

**Limitations**

The overall deltaBLEU scores across all approaches remain relatively modest, ranging from 5.70 to 13.04, which underscores the inherent complexity of medical visual question answering tasks, particularly in the specialized domain of wound care assessment. These moderate performance levels highlight fundamental challenges that must be addressed before such systems can provide meaningful clinical utility. Upon detailed examination of model outputs, we observed that while the systems demonstrate competency in identifying general wound characteristics and providing contextually appropriate clinical guidance, they frequently struggle with precise clinical terminology and specific wound classification. The models often generate responses that capture the general clinical context but may lack the precision required for definitive diagnostic support, similar to how they might correctly identify inflammatory characteristics while being less accurate in distinguishing between closely related wound types or infection stages that require different treatment protocols.

The variability in inter-annotator agreement scores reveals fundamental challenges inherent in the dataset itself, which directly impact model training and evaluation reliability. While features like wound type (IAA: 1.0) and tissue color (IAA: 0.97) show excellent agreement, the lower agreement for anatomical location (IAA: 0.81) and drainage amount (IAA: 0.86) suggests inherent subjectivity in clinical wound assessment that extends beyond simple annotation inconsistencies. This variability may reflect genuine clinical complexity, as wound characteristics often exist on continua rather than discrete categories, making it challenging for models to learn consistent decision boundaries. Furthermore, the dataset's scope may be limited in representing the full spectrum of wound presentations encountered in clinical practice, and the performance degradation observed when certain metadata categories are removed indicates potential dataset imbalances or insufficient representation of diverse wound presentations.

The methodological approaches employed in this study present several constraints that may have limited optimal performance. The two-stage pipeline approach in our metadata ablation study, while theoretically sound, appears to suffer from error propagation between metadata prediction and response generation phases, where inaccuracies in the initial metadata prediction cascade into the final response quality. The conservative confidence threshold (0.7) implemented may have been overly restrictive, limiting the integration of potentially valuable clinical insights and preventing the system from leveraging ambiguous but clinically relevant information. Additionally, the disparity in optimal context utilization across different models—requiring 5-shot prompting for MedGemma-27B versus 25-shot prompting for InternVL3-38B—suggests that current few-shot learning strategies are highly model-dependent and may require more systematic optimization approaches tailored to specific architectural characteristics.

The gap between semantic similarity metrics and clinical accuracy presents a significant concern for practical deployment. While BERTScore consistency indicates that models maintain coherent medical discourse, the modest deltaBLEU scores suggest they may not achieve the diagnostic precision necessary for clinical decision support. This discrepancy is particularly problematic in wound care, where treatment decisions often hinge on subtle clinical distinctions that our current approaches may not adequately capture. The models' tendency to provide generally appropriate clinical context while missing specific diagnostic details could potentially lead to suboptimal treatment recommendations or delayed appropriate interventions in real clinical settings.

Current evaluation frameworks may not fully capture the complexities of clinical utility and decision-making processes. The reliance on text-based similarity metrics, while providing standardized comparison methods, may not adequately reflect the nuanced clinical reasoning required for effective wound care assessment. The evaluation approach does not account for the hierarchical importance of different types of clinical information—where certain diagnostic errors may have more severe clinical consequences than others—nor does it assess the models' ability to appropriately express uncertainty when faced with ambiguous presentations. Additionally, the absence of longitudinal assessment data limits our understanding of how these systems might perform in tracking wound healing progression or adapting recommendations based on treatment responses, which are critical components of comprehensive wound care management in clinical practice.

**8. Conclusion**

This study evaluated three distinct approaches for wound care visual question answering, revealing significant challenges and opportunities in medical multimodal AI systems. MedGemma-27B with few-shot prompting achieved the highest performance (deltaBLEU: 13.04), demonstrating the value of domain-specific medical training over general-purpose multimodal architectures. The metadata ablation study identified anatomical location, wound type, and tissue color as critical features for wound assessment, with their removal causing substantial performance degradation. However, the overall modest deltaBLEU scores (5.70-13.04) underscore the inherent complexity of medical visual question answering tasks and highlight the substantial improvements required before clinical deployment.

The variability in inter-annotator agreement scores across wound attributes reflects genuine clinical complexity rather than simple annotation inconsistencies, emphasizing the subjective nature of certain wound characteristics. While models demonstrated competency in generating contextually appropriate clinical guidance, they frequently struggled with precise diagnostic terminology and specific wound classification—critical requirements for effective clinical decision support.

Future research should prioritize hybrid architectures that combine multimodal reasoning capabilities with specialized medical knowledge, develop more sophisticated uncertainty quantification methods, and establish evaluation frameworks that better align with clinical decision-making processes. Enhanced datasets incorporating diverse wound presentations and longitudinal treatment data, coupled with comprehensive clinical validation studies, are essential steps toward developing systems that can meaningfully contribute to healthcare practice. The gap between current performance and clinical requirements necessitates continued interdisciplinary collaboration between AI researchers and healthcare professionals to address these fundamental challenges.

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