Advancing Clinical NLP with RoBERTa & BART

From Classification to Summarization: Unveiling New Insights

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1 Abstract

In this retrospective study aligned with MediQA-Chat-2023 (from the ACL Clinical-NLP conference) [4], I present a unique approach to classifying and summarizing medical dialogues while prioritizing data privacy and computational efficiency. This project, conducted outside the conference, utilizes an ensemble model for classification (Task A1) and a fine-tuned BART model with SAMSum dataset for summarization (Task A2) [9], demonstrating the effectiveness of combining *unprompted training with prompted inference*. Despite not using public LLMs like GPT or Cohere and not having augmented data from Task C, the methods achieved competitive results, with top-tier scores for Task A1 and top 10 for Task A2, highlighting the robustness and practicality of the approach. This work, undertaken with the aim of contributing to ongoing discussions in the field , underscores the feasibility of using LLMs responsibly in sensitive domains and sets a groundwork for future research covering a more comprehensive analysis.

2 Introduction

Recent advancements in clinical natural language processing (NLP) have spotlighted the importance of summarizing doctor-patient conversations effectively [13]. This complex task involves condensing doctor-patient conversations into concise, informative summaries, aiding medical practitioners in assimilating key points from past interactions ([17]). The unique challenges of this task arise from the necessity to comprehend complex dialogues often constrained by limited data availability and the sensitive nature of med-

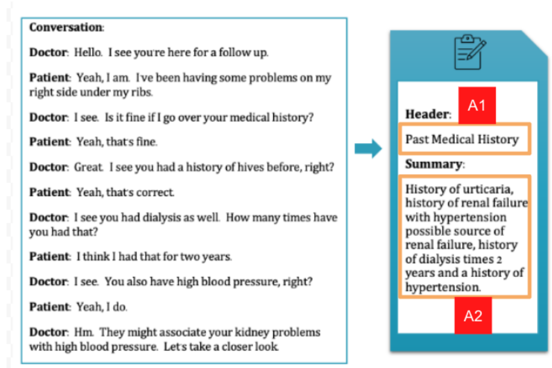

Figure 1: Task A: Header and Summary

ical information ([24]).

This task is critical for reducing doctors' workload and improving patient interactions. The MEDIQA-Chat 2023 initiative has played a significant role in advancing research in this area, focusing on automatic summarization and generation of doctor-patient conversations for data augmentation [4].

Large Language Models (LLMs) like GPT-4 have shown promise in medical dialogue summarization, but their application in clinical settings demands careful adaptation and scrutiny [11]. The challenge lies in the unstructured nature of medical conversations and the need to accurately identify key information across multiple symptom sets [18]. Various teams have employed different strategies for this task, including novel N-pass strategies, data augmentation techniques, and fine-tuning on existing language models like T5, BART, and BioGPT [24]; [3].

Category	Description
ALLERGY	Documented allergies, particularly to medications, including adverse reactions.
ASSESSMENT	Physician's interpretation and summarization of patient's health issues.
CC (Chief Complaint)	Primary reason for the patient seeking medical attention.
DIAGNOSIS	Final diagnosis determined by the physician based on evaluation.
DISPOSITION	Patient's status at the end of the visit and instructions for follow-up.
EDCOURSE	Details of the patient's experience and treatment in the emergency department.
EXAM	Findings from the physical examination, covering various systems.
FAM/SOCHX	Patient's family health history and social lifestyle factors.
GENHX	General history including the history of present illness and demographics.
GYNHX	Patient's gynecological and obstetrical history, if applicable.
IMAGING	Results and findings from diagnostic imaging studies.
IMMUNIZATIONS	Record of vaccinations and current immunization status.
LABS	Results from laboratory tests and their clinical interpretations.
MEDICATIONS	List of current medications and prescriptions being taken by the patient.
OTHER HISTORY	Additional relevant historical information not covered in other categories.
PASTMEDICALHX	Comprehensive history of the patient's past medical conditions.
PASTSURGICAL	Record of past surgical procedures the patient has undergone.
PLAN	Outline of the treatment plan including any recommended actions or follow-up.
PROCEDURES	Details of any medical procedures performed on the patient.
ROS (Review Of Systems)	Systematic review of each major body system.

Table 1: List of Categories (Task A1) in MEDIQA-Chat 2023

In this paper, I place a strong emphasis on data privacy, deliberately avoiding using public LLMs like GPT-4 & Cohere due to the sensitive nature of medical data. Of particular interest is the approach to Task A2 (summarization) which combines unprompted training with prompted inference, a technique commonly seen in GPT models, leading to a significant improvement in Task A2's average scores.

The experiments were conducted with a focus on developing cost-effective and production-ready services using prior-generation NVIDIA A10G Tensor Core GPUs. Despite the constraints of not participating in the conference and lacking augmented data from Task C, my methods yielded competitive results, highlighting the robustness of the approach under resource limitations.

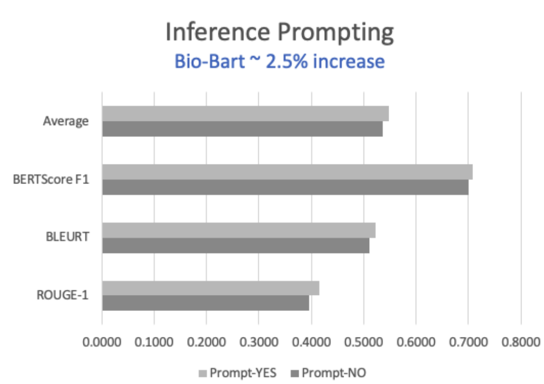

Figure 2: Key Project Insight: Inference Prompting

3 About MEDIQA-Chat 2023

The MEDIQA-Chat 2023 initiative, as detailed by Ben Abacha et al. (2023) [4], comprises a series of shared tasks aimed at fostering advancements in automatic clinical note generation from doctor-patient conversations. This initiative included three primary tasks: Short Dialogue2Note Summarization (Task A) [5], Full Dialogue2Note Summarization (Task B) [5], and Note2Dialogue Generation (Task C) [5]. My focus primarily lies in Task A, which involves generating a section summary, inclusive of both the section header and text, based on short snippets of doctor-patient conversation.

3.1 Task A1: Header Classification

Task A1 of MEDIQA-Chat 2023 presents the challenge of classifying short doctor-patient conversations into predefined section headers [4]. The task demands a nuanced understanding of the content to categorize each dialogue into one of twenty possible sections. These headers, which include categories like 'Allergy', 'Diagnosis', and 'Medications', form the basis of structuring clinical notes in a way that is both accessible and informative for healthcare providers [19]. The classification model's success hinges on its ability to discern subtle details within conversations and to align them with the corresponding section header that best encapsulates the discussion's focal points [8]. Table 1 provides a snapshot of the twenty classification categories used for Task A1, each representing a distinct facet of the clinical note-taking process.

3.2 Task A2: Dialogue Summarization

Task A2 expands upon the classification foundation laid by Task A1 and delves into the summarization of the doctor-patient dialogues [24]. The objective is to distill the essence of these conversations into concise, coherent summaries that are aligned with the classified section headers [18]. This task is intricate, as it involves not just the reduction of text but also the preservation of clinical relevance and the maintenance of narrative coherence [10]. The model must navigate complex medical terminologies, patient concerns, and diagnostic details to produce a summary that accurately reflects the content and context of the interactions [12]. Figure 1 depicts a schematic that encompasses both Task A1 and Task A2, illustrating the nature of classification and summarization in the generation of clinical notes [15].

4 Dataset Description

The MEDIQA-Chat 2023 dataset, provided by Ben Abacha et al. (2023) [4], comprises doctor-patient dialogue transcripts, each paired with section headers and summary notes, like Dialog-Sum [6]. This dataset is segmented into training, validation, and test sets. The training set includes 1,201 conversation pairs along with their corresponding section headers and summaries. The validation set contains 100 pairs, while the test set encompasses 200 conversations. These dialogues span across 20 diverse section headers, ranging from Medications and Review of Systems to Past Surgical History and more, offering a comprehensive representation of clinical scenarios [21].

Task	Dataset	Training	Validation	Test
A	MTS-Dialog	1,201	100	200
B	ACI-Bench	67	20	40
C	ACI-Bench	67	20	40

Figure 3: Task A: Data - MTS Dialog

For this project, I relied exclusively on the MTS-Dialog dataset as defined for Task A [5]. However, it is worth noting that additional datasets (Dialog-sum and Samsum) were tested during fine-tuning but discarded after no noticeable improvements were seen in preliminary research [9]. In addition to MIMIC-IV Notes, both these datasets will be considered for future research.

5 Evaluation Metrics

The evaluation of MEDIQA-Chat 2023 tasks leverages an ensemble of metrics for assessment [2]. ROUGE (Lin, 2004) [16], a basic metric in summarization, evaluates the F1 scores across ROUGE-1, ROUGE-2, ROUGE-L and ROUGE-L-Sum [12]. Complementing ROUGE, BLEURT scores (Sellam et al., 2020) [23] are employed to gauge semantic parallels between the generated and reference summaries [1]. Additionally, BERTScore (Zhang et al., 2020) [27] provides sentence-level semantic analysis. These metrics, carefully chosen based on their strong correlation with human judgment in clinical note generation, collectively offer a holistic evaluation perspective [3]. The average score derived from ROUGE-1, BLEURT-20, and BERTScore (microsoft/deberta-xlarge-mnli) serves as the primary criterion for ranking my results in Task A1, i.e., short note generation (Average-Score) [22].

For Task A, the evaluation also includes the accuracy of section header classification, adding another dimension to the assessment process.

6 Baseline Models

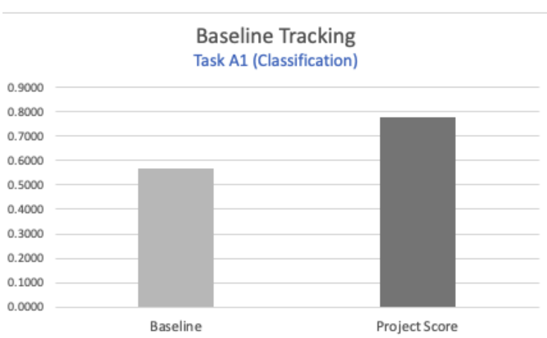

Figure 4: Task A1: Baseline

In my approach to establishing a baseline for the MEDIQA-Chat 2023 tasks, I followed the guidelines set forth by the workshop's authors, focusing on utilizing OpenAI's GPT-3.5-turbo. This decision was based largely on being compliant with the guidelines of the workshop.

Additionally, the current leaderboard includes a baseline using GPT-4, with which I have conducted tests as well. The results I obtained align closely with those from the existing baseline, GPT-3-Turbo.

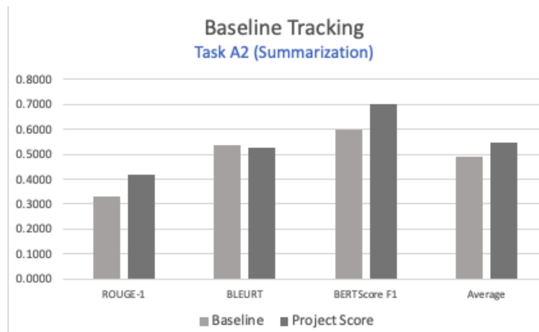

Figure 5: Task A2: Baseline

The baseline for both tasks was done using a single prompt which first classifies the conversation into a category such as FAMILY HISTORY/SOCIAL HISTORY, HISTORY OF PRESENT ILLNESS, PAST MEDICAL HISTORY, and so on and then, to provide a summary of the conversation in the style of a clinical note.

7 Solution

This paper details the development of a novel two-stage approach to tackle the challenges of medical dialogue classification and summarization. By leveraging the strengths of RoBERTa and Clinical Longformer for Task A1, the study achieved an classification accuracy of **0.78**, rivaling the highest scores at the conference. The methodology's success is attributed to the design and application of an arbitration process and the careful curation of model hyperparameters.

For Task A2, the research ventured into uncharted territory, applying prompt engineering to a BART-Samsum model traditionally used without prompts. This strategy led to a noticeable improvement in summarization quality, marking a departure from conventional BART applications and offering new insights into the versatility of transformer-based models in the clinical domain.

7.1 Task A1: Section Header

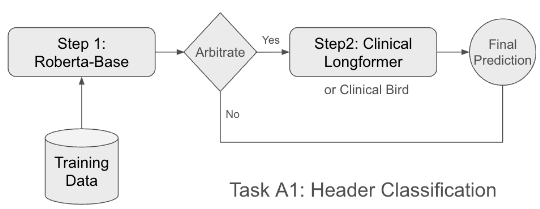

Figure 6: Task A1: Solution

For Task A1, I implemented an ensemble model merging RoBERTa and Clinical Longformer (alternatively, Clinical BigBird). This model aimed to classify doctor-patient conversations into one of twenty categories with high precision. The challenge was considerable due to the complex nature of medical dialogues.

Step 1: Classification using RoBERTa: The initial stage involved fine-tuning RoBERTa for the 20-class problem. This model, trained to identify the most likely category for each conversation, achieved an accuracy of **0.77**. The dialogues underwent tokenization and processing through RoBERTa-Base, yielding category predictions. These were then compared to actual labels to assess accuracy.

Step 2: Arbitration & Final Inference with Clinical Longformer: The second stage introduced an arbitration process, focusing initially on 'GENHX' and 'Medications'. Selected dialogues were reanalyzed using a fine-tuned Clinical Longformer model. This step refined predictions through detailed examination of specific dialogues, utilizing Longformer's extensive context analysis capabilities.

As shown in Table 2, this approach enhanced overall accuracy, achieving **0.78**, equating the conference's highest accuracy. The selection process for the second step's dialogues was adaptable, based on the first step's outcomes, highlighting potential areas for further exploration.

The ensemble model's success in achieving high accuracy in medical dialogue classification showcases the effectiveness of combining different model strengths. The flexible arbitration process between the two steps offers interesting research possibilities, emphasizing the ensemble method's potential in complex tasks like medical NLP.

7.2 Task A2: Section Summary

for Task A2, I developed a novel approach for section summary generation that focused exclusively on finetuning a BART-Samsum model with the Samsum dataset. This task involved the challenge of accurately summarizing complex medical dialogues.

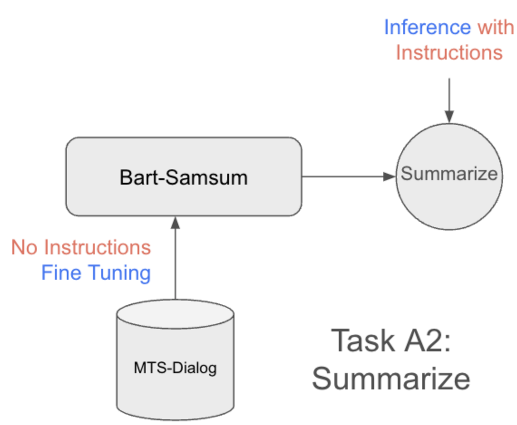

Figure 7: Task A2: Solution

Finetuning BART-Samsum (or Bio-Bart): The core of the solution centered around finetuning the BART-Samsum model, initially trained on the SAMSum dataset, specifically on the MTS-Dialog train-

Table 2: RESULTS: Task A1: Classification

Category	Label	Total Predictions	Correct Predictions	Precision	Total Actuals	Correct Actuals	Recall	F1
0	ALLERGY	11	11	1.000000	12	11	0.916667	0.956522
1	ASSESSMENT	5	4	0.800000	11	4	0.363636	0.500000
2	CC	9	5	0.555556	11	5	0.454545	0.500000
3	DIAGNOSIS	2	0	0.000000	1	0	0.000000	0.000000
4	DISPOSITION	2	1	0.500000	1	1	1.000000	0.666667
5	EDCOURSE	1	0	0.000000	4	0	0.000000	0.000000
6	EXAM	8	3	0.375000	5	3	0.600000	0.461538
7	FAM/SOCHX	49	44	0.897959	45	44	0.977778	0.936170
8	GENHX	48	42	0.875000	53	42	0.792453	0.831683
9	GYNHX	1	1	1.000000	1	1	1.000000	1.000000
10	IMAGING	2	1	0.500000	1	1	1.000000	0.666667
11	IMMUNIZATIONS	1	1	1.000000	1	1	1.000000	1.000000
12	LABS	0	0	0.000000	1	0	0.000000	0.000000
13	MEDICATIONS	12	10	0.833333	10	10	1.000000	0.909091
14	OTHER$_{H}ISTORY$	0	0	0.000000	3	0	0.000000	0.000000
15	PASTMEDICALHX	24	13	0.541667	14	13	0.928571	0.684211
16	PASTSURGICAL	6	6	1.000000	7	6	0.857143	0.923077
17	PLAN	3	1	0.333333	1	1	1.000000	0.500000
18	PROCEDURES	0	0	0.000000	1	0	0.000000	0.000000
19	ROS	16	13	0.812500	17	13	0.764706	0.787879

ing dataset. This finetuning was conducted without the use of explicit prompts, relying solely on the dialogue data. During the inference phase, a carefully crafted prompt was introduced to the finetuned model. This method of prompt engineering during the inference stage represents a deviation from typical BART model usage, which generally does not involve prompts for summarization.

The inclusion of prompts during inference led to a notable improvement in the quality of the summarization, demonstrating a **2%-2.5%** increase in performance. This finding is meaningful as it contrasts with the common practice in GPT-style models, where prompt-based inference is more typical. Applying prompts in a BART-based model for summarization, which is generally prompt-agnostic, underscores a novel and effective application of prompt engineering in transformer-based models for medical dialogue summarization.

This approach, the results of which are in Table 3, streamlines the process into a single step of finetuning and inference with prompt engineering and simplifies the methodology while maintaining effectiveness. It demonstrates the potential of specialized model training combined with strategic prompting in enhancing the quality of medical dialogue summaries.

8 Ranking

8.1 Task A1: Header Classification

Team	Run#	Accuracy	Rank	Code Status
NUS-IDS	run1	**0.780**	1	1
WangLab	run2	**0.780**	1	1
WangLab	run3	0.770	3	1
HuskyScribe	run1	0.755	4	2
WangLab	run1	0.750	5	1
gersteinlab	run2	0.745	6	1
Cadence	run1	0.735	7	1
NewAgeHealthWarriors	run1	0.730	8	5
DFKI-MedIML	run2	0.725	9	1
DFKI-MedIML	run3	0.725	9	1
DFKI-MedIML	run1	0.725	9	1
HealthMavericks	run2	0.725	9	5
HealthMavericks	run3	0.725	9	5
HealthMavericks	run1	0.725	9	5
gersteinlab	run1	0.710	15	3
SummQA	run2	0.710	15	3
SummQA	run1	0.710	15	3
NewAgeHealthWarriors	run2	0.705	18	2
UMASS_BioNLP	run1	0.705	18	5
DS4DH	run2	0.700	20	5
DS4DH	run1	0.700	20	1
gersteinlab	run3	0.700	20	3

0.78 1st

Figure 8: Task A1: Ranking - partial

In Task A1 (figure 8), my project attained an ac-

Table 3: RESULTS: Task A2: Summarization

HuggingFace Model	Model Type	Rouge-1	BertScore-F1	BLEURT	AvgScore
20231130_BioBart-Base_5ep_Summ_Loss_0.76	Bio-Bart	0.4145	0.7086	0.5226	0.5486
20231205_Bart-lg-samsum_8ep_Summ_Loss_1.09	Bart-Samsum	0.4192	0.6986	0.5269	0.5482
20231130_BioBart-Base_10ep_Summ_Loss_0.77	Bio-Bart	0.4045	0.7196	0.5148	0.5463
20231205_Bart-lg-samsum_8ep_Summ_Loss_1.09	Bart-Samsum	0.4109	0.6910	0.5212	0.5410
20231129_Bart-Lg-samsum_3ep_Summ_Loss_0.81_R1_0.32	Bart-Samsum	0.4076	0.6939	0.5178	0.5398
20231130_BioBart-Base_5ep_Summ_Loss_0.76	Bio-Bart	0.4037	0.6986	0.5122	0.5382
20231207_Step_98_Retrain_Instrn_Bart-S_9ep_Loss_0.42	Bart-Samsum	0.3901	0.6916	0.5079	0.5299
20231207_Step_101_Retrain_Augmn_Instrn_BioBart_Xep_Loss_0.45	Bio-Bart	0.3796	0.6911	0.5097	0.5268
20231201_Clinic-T5-Lrg_9ep_Summ_Loss_0.93	Clinical-T5	0.3434	0.6535	0.4979	0.4982
20231130_Clinic-T5-Sci_20ep_Summ_Loss_0.84	Clinical-T5	0.3025	0.6300	0.4627	0.4651
20231130_Clinic-T5-Base_18ep_Summ_Loss_0.85	Clinical-T5	0.2833	0.6240	0.4694	0.4589

curacy rate of **0.78**, matching the performance of leading group submissions. This is noteworthy given the project's constraints: it was completed within a shorter timeframe, as a solo endeavor, and without leveraging augmented data from Task C, a resource likely utilized by other teams to boost training effectiveness. Furthermore, the results was realized without relying on public Large Language Models (LLMs) such as GPT-4 or Cohere, adhering to data privacy considerations. The project's result may be attributed to strategic use of ensemble models and carefully selection of hyperparameters.

8.2 Task A2: Header Summary

For Task A2 (figure 9), which focused on section summary, my model's performance varied between the 5th and 13th positions when compared to current team benchmarks, depending on the metric being considered, such as ROUGE-1 [16] or average score. This variation can be observed despite the mentioned project constraints mentioned above. Of particular interest is the fact that all scores increased w.r.t the baseline, with the exception of the BLEURT [23] – pointing to an area of future research.

9 Limitations

While several models were tested, this study does not cover the entire spectrum of methods for generating clinical notes. The constraints of the utilized dataset in terms of size and diversity of medical specialties indicate the need for broader validation. A significant limitation was the lack of external medical knowledge integration, which could enhance task performance. Furthermore, the development faced challenges due to limited access to advanced computational resources and reliance on publicly available datasets which necessitated innovative approaches like prompt engineering. The observed variability in generated summaries highlights the need for more stable and deterministic outputs in clinical applications.

10 Ethics Statement

Ethical considerations, especially privacy, are central to the development of automated systems for clinical note generation. This project's focus on privacy is reflected in my decision to avoid using public LLMs like GPT-4, emphasizing data confidentiality and compliance with legal and ethical standards. Ensuring informed consent, where patients understand and control the use of their data, is crucial. The system's design aims to avoid biases and mitigate healthcare disparities while prioritizing accuracy and reliability to avoid adverse impacts on patient care. Upholding a strong ethical framework is imperative in developing systems that respect patient privacy and maintain the highest standards of patient care and ethical conduct in healthcare.

Team	Run#	ROUGE-1	ROUGE-2	ROUGE-L	ROUGE-LSum	BERTScore	BLEURT	Agg-Score	Agg-Rank	Code Status
WangLab	run2	**0.4466**	**0.2282**	**0.3837**	**0.3837**	**0.7307**	0.5593	**0.5789**	1	1
WangLab	run3	0.4396	0.1999	0.3781	0.3781	0.7260	0.5570	0.5742	2	1
SummQA	run1	0.4216	0.2017	0.3478	0.3478	0.7247	**0.5753**	0.5739	3	3
Cadence	run1	0.4303	0.2078	0.3642	0.3642	0.7187	0.5377	0.5622	4	1
WangLab	run1	0.4160	0.2003	0.3512	0.3512	0.7203	0.5464	0.5609	5	1
SummQA	run2	0.4056	0.1920	0.3317	0.3317	0.7030	0.5666	0.5584	6	3
gersteinlab	run3	0.4011	0.2147	0.3322	0.3322	0.7058	0.5421	0.5497	7	1
NewAgeHealthWarriors	run1	0.3983	0.1717	0.3314	0.3313	0.6982	0.5350	0.5438	8	5
UMASS_BioNLP	run2	0.3828	0.1828	0.3158	0.3166	0.7015	0.5405	0.5416	9	5
gersteinlab	run1	0.3882	0.1966	0.3214	0.3214	0.700	0.5294	0.5392	10	1
gersteinlab	run2	0.3882	0.1966	0.3214	0.3214	0.700	0.5294	0.5392	10	1
NewAgeHealthWarriors	run2	0.3780	0.1707	0.3134	0.3134	0.6926	0.5303	0.5336	12	2
Calvados	run1	0.3946	0.1864	0.3321	0.3321	0.6999	0.4724	0.5223	13	1
NUS-IDS	run1	0.3511	0.1538	0.2843	0.2843	0.6689	0.5411	0.5204	14	1
HuskyScribe	run1	0.3689	0.1820	0.3072	0.3072	0.6837	0.5006	0.5177	15	1
Care4Lang	run1	0.3581	0.1650	0.2890	0.2890	0.6789	0.5143	0.5171	16	1
Care4Lang	run2	0.3447	0.1553	0.2808	0.2808	0.6726	0.5085	0.5086	17	2
Calvados	run3	0.3569	0.1598	0.2896	0.2896	0.6721	0.4698	0.4996	18	1
DS4DH	run1	0.3080	0.1197	0.2424	0.2424	0.6644	0.5206	0.4977	19	3
clulab	run1	0.3414	0.1379	0.2842	0.2842	0.6569	0.4876	0.4953	20	1
clulab	run2	0.3414	0.1379	0.2842	0.2842	0.6569	0.4876	0.4953	20	1
Calvados	run2	0.3604	0.1617	0.3057	0.3057	0.6779	0.4449	0.4944	22	1
Care4lang	run3	0.3322	0.1400	0.2830	0.2830	0.6582	0.4856	0.4920	23	2
UMASS_BioNLP	run1	0.3283	0.1351	0.2743	0.2743	0.6699	0.4757	0.4913	24	5
HealthMavericks	run2	0.2973	0.1357	0.2200	0.2200	0.6120	0.4956	0.4683	25	5
HealthMavericks	run3	0.2514	0.1011	0.2002	0.2002	0.6268	0.5015	0.4599	26	5
DS4DH	run2	0.2937	0.1091	0.2135	0.2135	0.6179	0.3887	0.4334	27	5
HealthMavericks	run1	0.1987	0.0867	0.1560	0.1560	0.5703	0.4298	0.3996	28	5
DFKI-MedIML	run3	0.1931	0.0771	0.1784	0.1784	0.5758	0.3700	0.3796	29	1
DFKI-MedIML	run2	0.1818	0.0727	0.1707	0.1707	0.5656	0.363	0.3701	30	1
DFKI-MedIML	run1	0.1762	0.0656	0.1641	0.1641	0.5612	0.3664	0.3679	31	1
Baseline1	ChatGPT	0.3032	0.1209	0.2420	0.2420	0.6597	0.5032	0.4887	-	1
Baseline2	GPT-4	0.3071	0.1283	0.2365	0.2365	0.6484	0.5292	0.4949	-	1

Figure 9: Task A2: Ranking - partial

11 Conclusion and Future Work

The research presented in this paper, aligned with the MediQA2023-Chat challenge, showcases the adaptability and potential of current NLP technologies in medical dialogue summarization and classification. The development of an ensemble model for Task A1 and the novel use of prompted inference in a fine-tuned BART model for Task A2 demonstrate the feasibility of achieving competitive results under constraints such as limited computational resources and stringent data privacy. These methodologies, avoiding the use of public LLMs and augmented data, highlight the project's effectiveness and innovation.

Moving forward, the focus will shift towards expanding this research to encompass Tasks B and C, aiming to delve deeper into the realm of clinical NLP. Future work will explore ensemble methods combining extractive and abstractive summarization techniques to enhance summary quality. The potential integration of public instruction-based models or private models, subject to resource availability, will also be considered. This progressive agenda is designed to address existing limitations and push the boundaries in clinical NLP, contributing to advancements that are both technically robust and ethically grounded, ultimately fostering improvements in patient care through advanced NLP applications.

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