STM JOURNALS

Journal of
Artificial Intelligence
Research & Advances

ISSN: 2395-6720
Volume 12, Issue 2, 2025
May–August
DOI Journal: 10.37591/JoAIRA

https://journals.stmjournals.com/joaira

Research JoAIRA

Bridging the Gap and Unlocking Health Literacy: A Guide to Medical Report Clarity

Devanshi Prajapati[1,*], Pranjal Roy Vishwakarma[2], Bhawana Pillai[3], Vinod Patel[4]

Abstract

This research highlights the significant challenges faced by the general population in interpreting laboratory reports, medical charts, and other health-related documents. Studies show that approximately 9 out of 10 individuals struggle to understand such medical information, primarily due to low health literacy levels. This lack of understanding has become a hidden epidemic, affecting the way people engage with and respond to their own healthcare. While medical tests are essential for diagnosing illnesses, tracking disease progression, and evaluating treatment efficacy, their interpretation typically requires expertise in the medical field. This raises an important concern: how can the average person make sense of complex medical data? To address this issue, the proposed research introduces a framework that leverages advanced technologies such as transformer models, sequence-to-sequence (Seq2Seq) learning, natural language processing (NLP), text summarization, and model fine-tuning. The goal is to simplify complex health data, enabling individuals to interpret their medical reports more clearly and confidently, thereby promoting better health decisions and outcomes.

Keywords: Transformer models, Seq2seq, text summarization, natural language processing and finetuning

INTRODUCTION

Medical reports are often filled with a vast number of technical phrases, specialized terms, and a high density of semantically complex language. These documents frequently contain non-expanded acronyms, shorthand abbreviations, and symbols that are commonly understood only by trained medical professionals. For the average person, interpreting such documents can be a daunting task, often leading to confusion or misinterpretation. Despite being crucial for patient care, diagnosis, and treatment planning, medical reports are not typically designed with the general public in mind.

In essence, these reports serve as essential communication tools between healthcare providers, yet they inadvertently create a communication barrier between doctors and patients. This linguistic gap limits patients' ability to fully understand their own health conditions, laboratory test results, or treatment recommendations. Consequently, many individuals are left feeling anxious or uninformed, simply because the language used in their reports is inaccessible to them. However, in today's rapidly evolving technological landscape, we are beginning to see promising solutions to this longstanding problem. With the integration of advanced

***Author for Correspondence**
Devanshi Prajapati
E-mail: pdevanshi485@gmail.com

[1]Research Scholar, Department of Computer Science and Engineering, Lakshmi Narain College of Technology and Science (LNCTS), Bhopal, Madhya Pradesh, India
[2]Data Engineer, Department of Computer Science, Pune, Maharashtra, India
[3]Professor, Department of Computer Science and Engineering, Lakshmi Narain College of Technology and Science (LNCTS), Bhopal, Madhya Pradesh, India
[4]Assistant Professor, Department of Computer Science and Engineering, Lakshmi Narain College of Technology and Science (LNCTS), Bhopal, Madhya Pradesh, India

Received Date: February 04, 2025
Accepted Date: March 30, 2025
Published Date: April 16, 2025

Citation: Devanshi Prajapati, Pranjal Roy Vishwakarma, Bhawana Pillai, Vinod Patel. Bridging the Gap and Unlocking Health Literacy: A Guide to Medical Report Clarity. Journal of Artificial Intelligence Research & Advances. 2025; 12(2): 31–36p.

technologies such as transformer-based models, natural language processing (NLP), and intelligent text summarization, there is a growing opportunity to break down these linguistic barriers. These tools have the potential to automatically interpret, simplify, and summarize complex medical documents into plain language that can be easily understood by non-experts [1].

This study aims to explore how such emerging technologies can be effectively utilized to demystify medical reports. Our goal is to demonstrate how artificial intelligence and machine learning are not just reshaping the future of healthcare delivery, but also enhancing medical literacy and empowering patients by making healthcare information more transparent, comprehensible, and accessible to all [2].

RELATED WORK

Numerous studies detailing the benefits of automatic text summarization in a range of fields, including biomedicine and healthcare, have been published in recent years. This relates directly to how medical personnel may better serve patients by text summarizing of medical papers, how it can save researchers time, etc. The fact that these automatically generated text summaries of the original papers may give the general notion of what is contained therein without requiring the reader to read the original documents lends credence to the success of this ideology [3].

These studies vary from one another based on number of variables, including the summarization's goal, the type of input document or documents, and the techniques employed to condense them. Depending on the requirement, the summaries produced may be extractive or abstractive. The finest available scientific data should guide healthcare decisions for both public health policies and individual individuals [4].

Evidence is necessary for both clinical practice and public health decision-making by primary care physicians. Good reviews, which are a cutting-edge synthesis of the available data on a particular study subject, provide the proof. Review articles are essential to decision-making in evidence-based medical practice because of the deluge of medical literature and the constant lack of time. The ability to save, exchange, and manage documents digitally has had a significant impact on the healthcare sector. This has improved patient care and increased prospects for medical research by making it simpler to find and share crucial data. With the advent of deep learning and transformer-based networks, which have significantly expanded the industry in recent years, it has become more and more vital to summarize the vast amounts of data that are available to both patients and physicians [5].

One article provides a thorough analysis of the methods and developments in language-model-based medical summarization. Three deidentified large medical text datasets, DISCHARGE, ECHO, and RADIOLOGY, are presented in a Chinese study on medical summarization. These datasets contain 50K, 16K, and 378K pairs of report and summary that are derived from MIMIC-III, respectively [6].

St. George's University research indicates that there are roughly 20 main medical specialties. Depending on the healthcare system in each nation, this number may alter. Some of them, like endocrinology, dentistry, and radiology, are so dissimilar from one another that it takes a lot of expertise, years of translating experience, and effective terminology management to switch [7].

METHODS AND MATERIALS

Transformer Model

The proposed study makes use of transformer model which has self-attention mechanisms and feedforward neural networks to process provided input data. Following steps are needed to work with a transformer model. Input embedding, positional encoding, multi-head attention, layer normalization and residual connection, feedforward neural networks [8].

Seq2Seq Model

This model helped to take sequential data as input and generate sequential data as output.

Text2text Generation

A flexible and effective method in Natural Language Processing (NLP) is text2text creation, which converts one text into another. This can involve activities including summarizing, translating, responding to inquiries, and more. With its Transformers library, Hugging-Face, a top supplier of NLP technologies, provides a powerful pipeline for Text2Text production [9].

Text Summarization

The term "automated text summarization" describes a group of techniques that use algorithms to distill large amounts of textual data while maintaining the essential ideas presented in the text. Through the development of simpler and more approachable language structures in medical documentation, this area of computer automation has made difficult medical jargon understandable to those without a medical experience [10]. Following are the steps done to accomplish the task:

1. *Loading the dataset:* We will use the Datasets library to download the data and get the metric we need to use for evaluation. Following dataset is used: https://huggingface.co/datasets/Bilal-Mamji/Medical-summary.
2. *Preprocessing the data:* We had preprocessed the texts before we can feed them into our model. This is accomplished by a Transformers Tokenizer, which will both produce the additional inputs the model needs and tokenize the inputs and format them in a way the model expects (Figure 1).
3. *Fine-tuning a model:* Now, since our data is ready, we can download the pretrained model and fine-tune it. Initially, we have fine-tuned a t5-large transformer model (https://huggingface.co/Falconsai/medical_summarization). Here is the fine-tuned model which is majorly inclined towards medical domain: https://huggingface.co/smiling-pranjal/medical_summarization-finetuned-Medical-summary.
4. *Visualizing the dataset distribution:* https://colab.research.google.com/drive/1J_fxFfEeu-PNZWXuQ8Q-0G_0ESUvazbt#scrollTo=FBiW8UpKIrJW.

RESULTS AND DISCUSSION

The medical report or any healthcare document is given as input which gives output in the form of SOAP summary. In the following way output is generated (Figure 2):

1. *S: Subjective:* A synopsis of the patient's symptoms, including the primary complaint and pertinent medical history, is provided here. In this case, the patient's remarks guarantee uniform language and act as the main source.

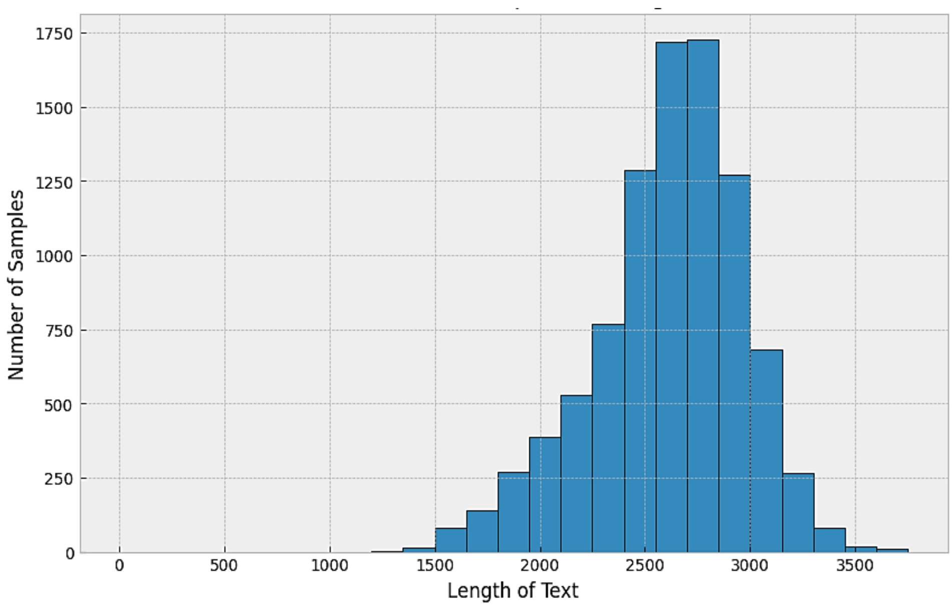

Figure 1. Distribution of input text lengths.

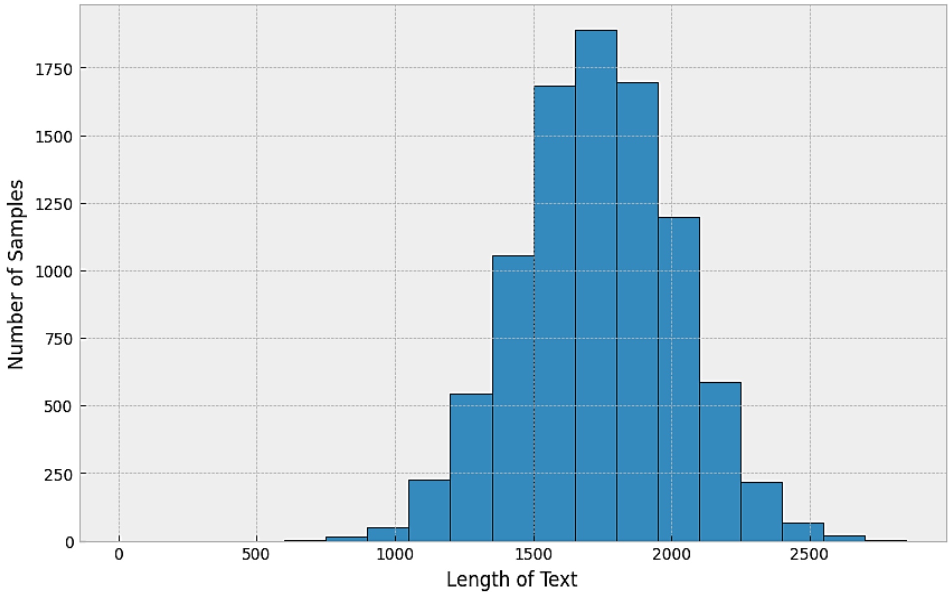

Figure 2. Distribution of output text lengths.

2. *O: Objective:* This section summarizes essential data, including imaging, lab results, and vital signs. It also highlights pertinent information, such as the side of the body affected and particular doses, and, where applicable, it offers normal ranges.
3. *A: Assessment:* Provides a succinct evaluation that incorporates both objective and subjective information. Indicates the prognosis outlook, any complications, and the main diagnosis together with any differential diagnoses.
4. *P: Plan:* Describes the treatment strategy, including the food, medicine, counseling, and education. Makes careful to address compliance issues and includes any appropriate referrals to other specializations. Here document confidentiality is effectively maintained.

Following is the summary of report generated as output after feeding medical report as input:

S: The patient is a 38-year-old gravida 1 woman presenting with a chief complaint of irregular menses occurring every 2–3 months for the past 15 years and associated infertility. She reports a history of an early first trimester spontaneous abortion without clinical or pathological confirmation. The patient has undergone a laparoscopic appendectomy with concurrent right salpingectomy. She has no family history of irregular menses, infertility, or premature ovarian failure. She recalls being informed of a 46,XY karyotype by a fertility specialist in Russia.

O: The patient's height is 160 cm, weight is 55 kg, and BMI is calculated at 23. Vital signs are within normal limits. Physical examination shows normal female secondary sex characteristics with Tanner stage V breast development and pubic hair growth, without signs of hirsutism or clitoromegaly. Laboratory findings indicate premature ovarian insufficiency with elevated follicle stimulating hormone (104.9 mIU/ml), luteinizing hormone (35.5 mIU/ml), low estradiol (<5 pg/ml), and normal total testosterone (<12 ng/dl). Liver and thyroid function tests are normal. Peripheral blood karyotype analysis confirms a 46,XY karyotype.

A: The primary diagnosis is premature ovarian insufficiency, likely contributing to the patient's infertility and irregular menses, in the context of a 46,XY karyotype. Differential diagnoses could include other genetic or endocrine disorders affecting menstrual regularity and fertility.

P: Plan to continue monitoring hormone levels and refer the patient to a fertility specialist for further evaluation and management of premature ovarian insufficiency. Discuss potential treatment options to manage symptoms and improve fertility chances. Educate the patient about the implications of her condition and the importance of follow-up appointments. Encourage the patient to reach out with any further questions or concerns regarding her treatment plan.

CONCLUSION

This research has demonstrated the efficacy of transformer models in the domain of medical report summarization, highlighting their capacity to process complex medical information into coherent and concise summaries. The findings indicate that transformer-based architectures, particularly those fine-tuned for medical language processing, significantly enhance the quality of summaries generated from extensive clinical reports, thereby facilitating improved accessibility and comprehension of critical patient data.

Implications

The implications of this study are multifaceted. First, the successful application of transformer models underscores their potential to revolutionize the way healthcare professionals interact with clinical documentation. By providing succinct summaries, these models can alleviate the cognitive burden on clinicians, enabling common people to understand difficult medical terminologies and allow them to make more informed decisions in a timely manner. Furthermore, the ability to generate accurate and contextually relevant summaries could enhance communication among healthcare teams, ultimately leading to improved patient outcomes.

Limitation

Following are the limitations to this research work:

1. Although our model is quite good at summarizing medical texts, it might not do as well on other tasks involving natural language processing. For best results, users who wish to use this model for various purposes should investigate the optimized versions found in the model hub.
2. There is a need for proper data handling and data privacy for electronic health records of patients.
3. The output is not produced in other specific language like Spanish, French etc.

Future Scope

In terms of future research directions, there are several avenues worth exploring. First, further investigation into the fine-tuning of transformer models with domain-specific datasets could yield even more precise summarization capabilities tailored to various medical specialties. Additionally, incorporating multimodal data, such as imaging and laboratory results, into the summarization process could provide a more holistic view of patient health, enhancing the utility of the generated summaries. Furthermore, longitudinal studies assessing the impact of transformer-generated summaries on clinical outcomes and decision-making processes would provide valuable insights into the practical benefits and limitations of these technologies in real-world settings. Finally, ethical considerations surrounding the use of AI in healthcare must be addressed, ensuring that the deployment of such models adheres to principles of fairness, accountability, and transparency. We can expect future advancements in accuracy, fluency, and summarization tailored to audiences.

REFERENCES

1. Palex Group. (2022). Why Medical Terminology is Tough, and How to Tackle It? [Online]. Palexgroup.com. Available from: https://palexgroup.com/blog/medical-terminology-translation/
2. Jain R, Jangra A, Saha S, Jatowt A. A survey on medical document summarization. arXiv preprint arXiv:2212.01669. 2022 Dec 3.
3. Zheng G, Wang X, Liang J, Chen N, Zheng Y, Wang B. Efficiently Democratizing Medical LLMs for 50 Languages via a Mixture of Language Family Experts. arXiv preprint arXiv:2410.10626. 2024 Oct 14.
4. Li X, Lan L, Lahza H, Yang S, Wang S, Yang W, Liu H, Zhang Y. EAFP-Med: An efficient adaptive feature processing module based on prompts for medical image detection. Expert Syst Appl. 2024 Aug 1; 247: 123334.
5. The Devastator. (2023). Medical Conversation Corpus (100k+). [Online]. Kaggle.com. Available from: https://www.kaggle.com/datasets/thedevastator/medical-conversation-corpus-100k

6. Gero Z, Singh C, Xie Y, Zhang S, Subramanian P, Vozila P, Naumann T, Gao J, Poon H. Attribute Structuring Improves LLM-Based Evaluation of Clinical Text Summaries. arXiv preprint arXiv:2403.01002. 2024 Mar 1.
7. Shamshad F, Khan S, Zamir SW, Khan MH, Hayat M, Khan FS, Fu H. Transformers in medical imaging: A survey. Med Image Anal. 2023 Aug 1; 88: 102802.
8. Sun D, He J, Zhang H, Qi Z, Zheng H, Wang X. A LongFormer-Based Framework for Accurate and Efficient Medical Text Summarization. arXiv preprint arXiv:2503.06888. 2025 Mar 10.
9. Helwan A, Azar D, Ozsahin DU. Medical reports summarization using text-to-text transformer. In 2023 IEEE Advances in Science and Engineering Technology International Conferences (ASET). 2023 Feb 20; 01–04.
10. Agilandeeswari L, Dagar A, Deepthi A, Arangasakthivel R. Automatic Text Summarization for Medical Dataset-An Analysis. InInternational Conference on Intelligent Systems Design and Applications. Cham: Springer Nature Switzerland; 2023 Dec 11; 336–352.

