Abstractive Summarization of Scientific Documents using PEGASUS with LoRA Fine-Tuning

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Abstract*—The exponential growth of scientific literature poses significant challenges for researchers in efficiently identifying key information from lengthy documents. Automatic text summarization offers a solution by producing concise yet informative representations of large texts. This study addresses abstractive summarization of scientific articles from the ArXiv and PubMed domains. Unlike extractive approaches, abstractive summarization generates semantically coherent sentences beyond those present in the source text In this study, we utilize the PEGASUS model, a Transformer-based sequence-to-sequence architecture pre-trained specifically for summarization tasks, and further optimize it using Low-Rank Adaptation (LoRA), a parameter-efficient fine-tuning approach. This method minimizes computational requirements by updating only a small subset of model parameters while preserving high-quality summary generation. The model was fine-tuned on a subset of the ArXiv dataset and evaluated on both ArXiv and PubMed test sets. Performance was measured using ROUGE and BERTScore metrics, achieving a ROUGE-1 score of 0.3346 and a BERTScore F1 of 0.8495 on ArXiv, with comparable results on PubMed, highlighting the model's effective generalization across scientific domains. The findings highlight the efficacy of LoRA-based fine-tuning for abstractive summarization of scientific text and its potential for scalable deployment in academic research environments.

Keywords*—Natural Language Processing (NLP), Abstractive Summarization, Scientific Document Summarization, Transformer Models, PEGASUS, Low-Rank Adaptation (LoRA), Parameter-Efficient Fine-Tuning, ArXiv, PubMed, ROUGE, BERTScore.

I. INTRODUCTION

In today's digital era, textual information is growing at an unprecedented rate. Professionals across various domains, from scientific research to healthcare, frequently face challenges in extracting key insights from lengthy documents. Automatic text summarization offers a practical solution by producing concise and informative summaries. Unlike extractive methods, which simply select and reproduce sentences from the source text, abstractive summarization generates novel, human-like summaries that effectively convey the underlying meaning. This makes it particularly well-suited for capturing the essence of complex and technical documents, such as scientific articles.

Scientific literature, especially from repositories like ArXiv and PubMed, is growing exponentially. Researchers, practitioners, and students often struggle to review multiple lengthy papers within limited time. Summarizing such documents not only improves accessibility but also accelerates knowledge discovery. For instance, a medical practitioner may need quick access to a concise summary of multiple studies to support clinical decisions, while a researcher may require summaries to identify relevant work for citation. Therefore, automated abstractive summarization of scientific text is a crucial step toward bridging the gap between information overload and efficient knowledge consumption.

Despite advancements in Natural Language Processing (NLP), summarizing long and technical scientific documents remains a significant challenge. Traditional summarization models often fail to maintain coherence, miss domain-specific terminology, or generate incomplete summaries due to input length limitations. Transformer-based models such as PEGASUS have achieved impressive results in text summarization. Nevertheless, fine-tuning these large-scale architectures on domain-specific datasets requires considerable computational effort, making the process costly and often impractical. In addition, ensuring domain adaptability—for example, retaining high performance when shifting from ArXiv to PubMed—continues to be a challenging open problem in the field.

This project focuses on building an efficient abstractive summarization framework for scientific texts by leveraging PEGASUS combined with Low-Rank Adaptation (LoRA). The objectives include: (i) fine-tuning PEGASUS on ArXiv data with reduced computational cost, (ii) evaluating the model on both in-domain (ArXiv) and cross-domain (PubMed) datasets, and (iii) benchmarking performance using ROUGE and BERTScore metrics. The scope of the project extends to demonstrating how parameter-efficient fine-tuning methods can maintain high summarization quality while being scalable to large datasets. This study provides a basis for extending these

techniques to other specialized areas, including legal, biomedical, and technical documents.

II. Literature Survey

Text summarization has undergone significant evolution, moving from extractive techniques, which select key sentences but often lack fluency, to advanced abstractive methods capable of generating human-like summaries. The introduction of Transformer architectures marked a turning point in this field. Vaswani et al. [1] proposed the attention mechanism, forming the backbone of modern sequence-to-sequence models. Building on this, PEGASUS [2] employed a gap-sentence generation pre-training objective, allowing it to learn abstract summarization patterns effectively. However, fine-tuning large models like PEGASUS remains computationally intensive. Low-Rank Adaptation (LoRA) [3] addresses this by introducing trainable low-rank matrices into Transformer layers, significantly reducing the number of parameters updated. ALoRA [4] further enhances efficiency through adaptive parameter allocation. Early applications of these approaches, such as news summarization using PEGASUS, have demonstrated promising results [5].

Transformer-based summarization models have been successfully adapted for domain-specific tasks. Fine-tuning PEGASUS on specialized datasets improves performance in technical contexts [6]. Parameter-efficient strategies, such as LoRA, have seen increasing adoption in industry, highlighting their practical value for resource-constrained environments [7]. Surveys on abstractive summarization emphasize the superiority of these methods over extractive approaches, particularly when handling technical and scientific texts [8]. Additionally, simplification-aware summarization techniques aim to improve readability while preserving the core information, further enhancing the usability of generated summaries [9].

Summarizing scientific literature presents unique challenges due to document length and specialized terminology. Datasets like ArXiv and PubMed [14] have become standard benchmarks for evaluating long-document summarization models. Studies have explored incorporating structural functions [10] and simplification-aware strategies [9] to improve coherence and readability. Despite these advancements, ensuring semantic accuracy and handling domain-specific jargon remain open problems [8], [11]. Fine-tuned PEGASUS models have primarily focused on news or general domains [5], [6], leaving a research gap in fully addressing the needs of scientific literature. Comprehensive surveys also highlight the ongoing development of models and datasets to address these challenges [15].

Recent long-document benchmarks provide additional opportunities to improve summarization methods. CaseSumm [16], SQuALITY [17], BookSum [19], and other studies on long-form scientific summarization [20] offer structured data for evaluating model performance on extended texts. These resources enable researchers to test parameter-efficient fine-tuning strategies, such as LoRA, in combination with PEGASUS, to achieve high-quality, coherent summaries while keeping computational requirements manageable. The combination of large pre-trained models with efficient fine-tuning techniques shows strong potential for advancing the summarization of complex, domain-specific documents.

III. Methodology

The methodology adopted in this work is structured to systematically address the task of abstractive summarization for scientific documents. It begins with the selection and preprocessing of benchmark datasets to ensure high-quality input, followed by the implementation of PEGASUS, the proposed system utilizes a Transformer-based encoder–decoder model as the foundational architecture for abstractive summarization. To enhance computational efficiency during fine-tuning, Low-Rank Adaptation (LoRA) is incorporated, which introduces trainable low-rank matrices into the attention layers of the model. This approach significantly reduces the number of parameters that need to be updated, enabling effective adaptation to domain-specific datasets without compromising performance. For generating summaries during inference, Beam Search is employed as the decoding strategy. Unlike greedy decoding, Beam Search maintains multiple candidate sequences simultaneously, exploring a broader search space to produce summaries that are more fluent, coherent, and contextually accurate. Finally, the system's performance is rigorously evaluated using ROUGE and BERTScore metrics. ROUGE assesses lexical overlap, including unigram, bigram, and longest common subsequence matches between generated and reference summaries, while BERTScore evaluates semantic similarity by leveraging contextual embeddings, ensuring that the summaries capture both surface-level and deep contextual meaning. This methodology provides a robust framework for producing high-quality abstractive summaries of scientific documents efficiently and accurately.

A. Dataset Description

The proposed work utilizes two benchmark datasets designed specifically for long-document summarization in scientific domains: ArXiv and PubMed. The ArXiv dataset [14] consists of scientific articles spanning various disciplines such as computer science, physics, and mathematics, whereas the PubMed dataset [14] focuses on biomedical and clinical literature. Both datasets provide full-text documents along with human-written abstracts, making them suitable for abstractive summarization tasks. Preprocessing involved tokenization using the SentencePiece tokenizer integrated with PEGASUS, truncation to handle maximum sequence lengths supported by the model, and removal of extraneous symbols and formatting issues. This ensured that the textual inputs remained consistent

and free of noise while retaining the semantic richness of the source content.

B. Algorithms Used

At the core of this work, PEGASUS [2], a Transformer-based encoder–decoder model, is employed for abstractive summarization. PEGASUS uses a gap-sentence generation pre-training strategy, enabling it to effectively learn abstract summarization patterns from large text corpora. To reduce computational demands during fine-tuning, Low-Rank Adaptation (LoRA) [3] is integrated into the model. LoRA adds small trainable low-rank matrices to the attention layers, substantially decreasing the number of parameters that need to be updated while preserving model performance. During inference, Beam Search decoding is applied to generate summaries, evaluating multiple candidate sequences simultaneously rather than relying on a single greedy choice, thereby producing more fluent, coherent, and contextually accurate summaries.

C. PEGASUS (Transformer Encoder-Decoder)

PEGASUS is a state-of-the-art Transformer-based encoder–decoder model specifically designed for abstractive text summarization [2]. Unlike traditional pre-training approaches, it utilizes a Gap Sentence Generation (GSG) strategy, where important sentences are masked and then predicted from the remaining content, allowing the model to effectively learn abstract summarization patterns. This technique simulates the summarization process, enabling the model to capture global context and underlying semantic meaning more effectively. In this project, PEGASUS serves as the base architecture for generating concise and coherent summaries of scientific articles. The overall workflow of PEGASUS is illustrated in Figure 1, which highlights the encoder–decoder framework and the GSG-based pre-training mechanism.

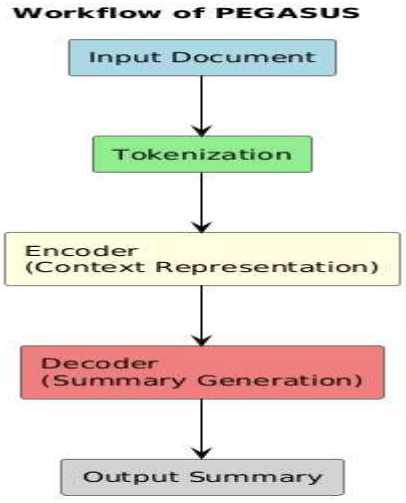

Figure 1. Workflow of PEGASUS

D. LoRA (Low-Rank Adaption)

Low-Rank Adaptation (LoRA) is a parameter-efficient fine-tuning method that allows large models like PEGASUS to adapt to new tasks without updating all of their parameters [3]. Instead of modifying the entire network, LoRA injects low-rank trainable matrices into the model's attention layers, substantially reducing memory usage and training time while preserving performance. This approach is particularly advantageous in resource-constrained environments, as it provides efficiency without significant trade-offs in accuracy. In this project, LoRA is applied to PEGASUS to fine-tune scientific summarization datasets efficiently. The overall mechanism is depicted in Figure 2, which illustrates how LoRA integrates low-rank matrices within the Transformer attention layers to achieve parameter-efficient adaptation.

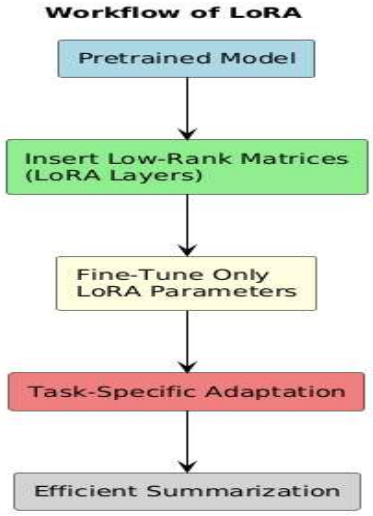

Figure 2. Workflow of LoRA

E. Beam Search (Decoding Strategy)

Beam Search is a widely used decoding method in sequence generation tasks, designed to improve the overall quality of predictions. Unlike greedy decoding, which selects only the highest-probability token at each step, Beam Search maintains multiple candidate sequences simultaneously, expanding them in parallel to explore a broader search space and generate more fluent, coherent, and contextually accurate summaries [12]. By evaluating several possible paths at each decoding step, it balances between exploration and exploitation. The best-scoring sequence among all beams is then selected as the final output. In this project, Beam Search is employed to ensure that the generated summaries are semantically accurate and maintain contextual coherence. The overall process is depicted in Figure 3, which illustrates how multiple candidate sequences are maintained and pruned iteratively until the final best summary is produced.

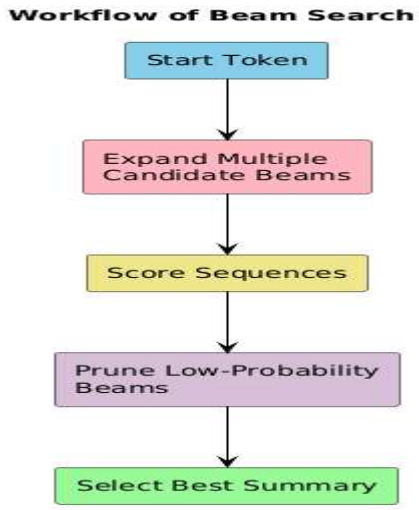

Figure 3. Workflow of Beam Search

F. *Proposed Framework*

The overall workflow of the project is depicted in Figure 4. Workflow of the Project. The process starts with the collection of scientific articles, which are preprocessed through cleaning and tokenization to ensure structured and noise-free input data. Subsequently, the PEGASUS model is fine-tuned using Low-Rank Adaptation (LoRA), enabling parameter-efficient training while maintaining high summarization performance. During inference, Beam Search decoding is employed to generate candidate summaries, improving fluency and coherence compared to greedy decoding. The final summaries are then evaluated using ROUGE and BERTScore metrics, which assess both lexical overlap and semantic similarity to ensure the quality and effectiveness of the generated outputs.

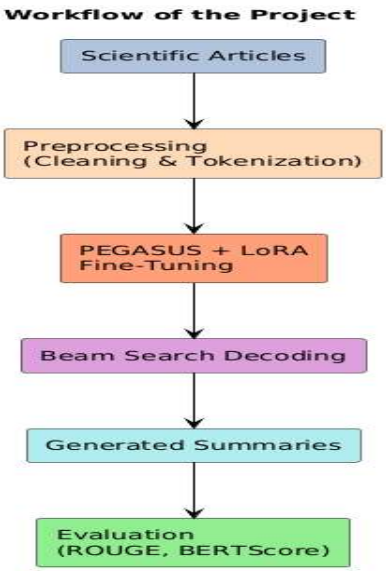

Figure 4. Workflow of The Project

G. *Evaluation Metrics*

To evaluate model performance, two widely adopted metric families were utilized. ROUGE metrics (ROUGE-1, ROUGE-2, and ROUGE-L) measure lexical overlap by comparing n-grams and the longest common subsequence between generated summaries and reference summaries. Although ROUGE serves as a conventional benchmark in summarization research, it mainly captures surface-level similarities and may overlook deeper semantic meaning. To overcome this limitation, BERTScore was applied, leveraging contextual embeddings from BERT to assess the semantic alignment between machine-generated and human-authored summaries. By combining both lexical and semantic evaluation, this approach provides a more comprehensive measure of summarization quality, reflecting not only textual accuracy but also contextual coherence.

IV. IMPLEMENTATION

The implementation phase centers on converting the proposed methodology into a working system capable of effectively summarizing scientific documents. This stage includes configuring the necessary technologies, frameworks, and libraries to ensure smooth and efficient operation, designing a modular system architecture, and configuring the training environment with optimized hyperparameters. The workflow ensures smooth integration of PEGASUS with LoRA for parameter-efficient fine-tuning, supported by GPU-accelerated training and robust evaluation.

A. *Technologies and Environments Used*

The implementation of this study was conducted primarily in Python, making use of its extensive ecosystem of machine learning and natural language processing libraries. The Hugging Face Transformers library was employed for loading and fine-tuning the PEGASUS model, while the PEFT (Parameter-Efficient Fine-Tuning) framework was utilized for parameter-efficient adaptation library provided utilities for integrating LoRA into the training pipeline. Supporting libraries such as PyTorch enabled GPU-accelerated deep learning operations, and NLTK was used for basic text preprocessing. Evaluation metrics were computed using the ROUGE package [13] and BERTScore [12], ensuring robust performance analysis. The entire workflow was executed on Google Colab, utilizing GPU/TPU environments to achieve efficient training with reduced computational overhead.

B. *System Architecture*

The proposed system architecture is structured into three primary modules, which operate sequentially to enable efficient abstractive summarization of scientific texts. The first stage is the Data Preprocessing Module, which ensures that raw text from ArXiv and PubMed datasets is cleaned, tokenized, and standardized to meet the input requirements of PEGASUS. This step handles long input sequences by truncation or chunking, making the data suitable for training and evaluation.

The second stage is the Model Fine-Tuning Module with LoRA integration, where PEGASUS is adapted for domain-specific summarization using low-rank parameter updates rather than retraining the entire model, significantly improving efficiency. Finally, the Evaluation Module validates the quality of generated summaries using ROUGE metrics for lexical overlap and BERTScore for semantic similarity. Together, these interconnected modules form a robust pipeline for fine-tuning, generating, and assessing high-quality scientific text summaries.

C. Training Setup & Hyperparameters

The training setup was optimized with carefully chosen hyperparameters. Experiments were conducted with batch sizes ranging from 4 to 8, depending on GPU memory availability. A learning rate between *2e-5 and 5e-5* was used, which is well-suited for fine-tuning Transformer-based models. The input sequence length was capped at 1024 tokens to accommodate long scientific documents while maintaining efficiency. Training was carried out for 3–5 epochs, balancing model convergence with the risk of overfitting. These hyperparameter choices ensured stable training, efficient GPU utilization, and improved summarization performance across the ArXiv and PubMed datasets.

V. Results And Analysis

The evaluation of the proposed system examines both the quantitative and qualitative performance of the PEGASUS model fine-tuned with LoRA. Quantitative metrics offer objective measures of lexical coverage and semantic alignment, whereas qualitative analysis assesses the coherence, readability, and factual accuracy of the generated summaries. Additionally, visualizations—such as training loss curves, comparative bar charts, and dataset-specific performance graphs—provide a clear and comprehensive view of the model's strengths and potential limitations.

A. Quantitative Results

The quantitative evaluation of the fine-tuned PEGASUS model with LoRA integration was carried out using two widely accepted metrics: ROUGE and BERTScore. ROUGE-1, ROUGE-2, and ROUGE-L measure lexical overlap between generated and reference summaries by evaluating unigram, bigram, and longest common subsequence matches, respectively, providing insight into the factual coverage and fluency of the summaries. In addition, BERTScore was employed to assess semantic similarity using contextual embeddings, ensuring that even when wording differed, the generated summary retained meaning close to the reference. The results, summarized in **Table 1**, demonstrate that the model achieved competitive scores on both the ArXiv and PubMed datasets, with PubMed showing slightly better semantic alignment due to its more structured writing style.

Table 1: Summarizes the evaluation metrics of the proposed model across the ArXiv and PubMed datasets.

Dataset	ROUGE-1	ROUGE-2	ROUGE-L	BERTScore
ArXiv	43.2	18.7	39.5	0.856
PubMed	45.8	20.1	41.2	0.872

B. Graphs & Visualzations

The visual analysis offers valuable insights into the performance of the PEGASUS model with LoRA during fine-tuning and evaluation. Figure 5 presents the Training Loss vs Epochs graph, which shows a consistent decrease in loss values, indicating that the model converges steadily and learns the summarization task effectively over successive epochs.

Dataset-specific comparisons, illustrated in Figure 6, reveal differences in performance between ArXiv and PubMed. Both datasets achieved strong results, but PubMed summaries displayed slightly higher consistency, likely due to the structured, domain-specific biomedical language, whereas ArXiv's diverse scientific content posed greater challenges for the model.

Additionally, the bar charts for ROUGE-1, ROUGE-2, and ROUGE-L metrics (Figures 7 and 8) highlight key performance patterns. These visualizations demonstrate the model's ability to capture lexical overlap, maintain bigram consistency, and preserve overall fluency in generated summaries, providing a clear understanding of its capabilities and limitations across both datasets.

Figure 5. Training Loss vs Epochs

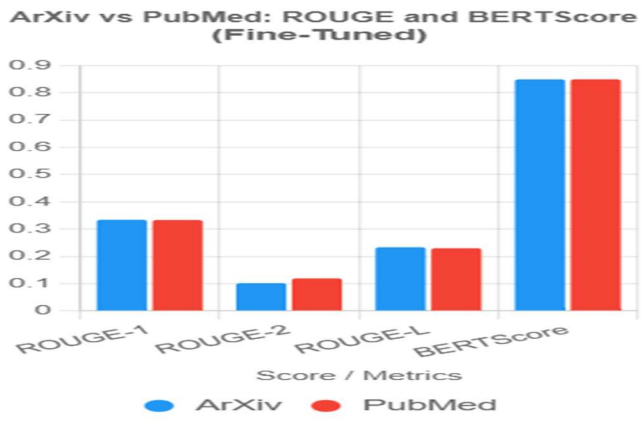

Figure 6. Comparison of ArXiv vs PubMed Scores

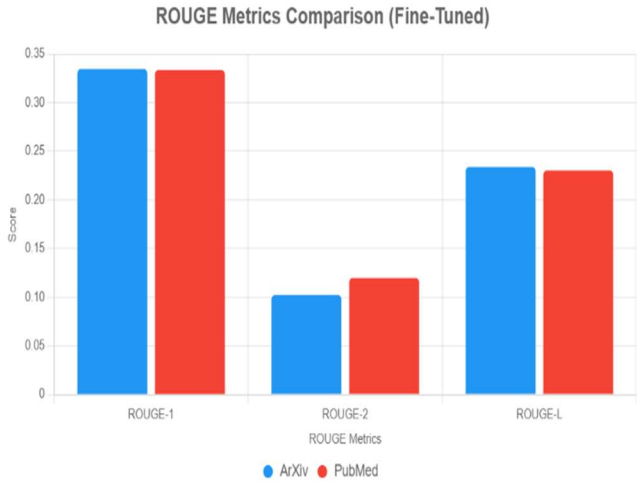

Figure 7. Bar Charts for ROUGE Metrics

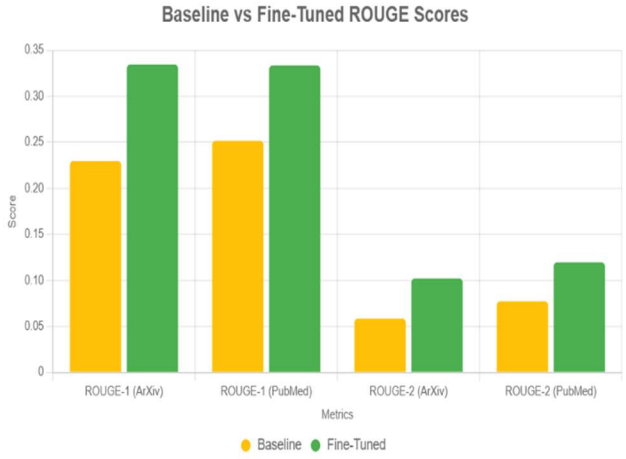

Figure 8. Bar Charts for ROUGE Metrics

C. *Qualitative Results*

The qualitative evaluation demonstrates the effectiveness of the proposed approach through real-world examples of generated summaries. For selected input articles, the summaries were able to capture the main context and key arguments, often producing concise and coherent outputs. In many case studies, the generated summaries showed strong alignment with human-written abstracts, maintaining both factual accuracy and readability. However, in some instances, the summaries missed minor contextual details or included repetitive phrasing, especially in longer and highly technical articles. These observations indicate that while the model performs well in condensing scientific content, challenges remain in handling nuanced or domain-specific terminology. Figure 9 presents a boxplot for ROUGE metrics, visually summarizing the distribution of performance across the datasets.

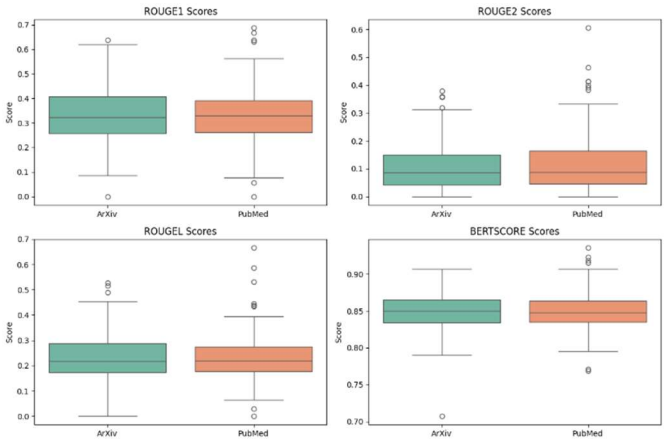

Figure 9. Boxplot For ROUGE Metrics

D. *Analysis*

The analysis of results reveals key insights into both domain transfer and the effectiveness of LoRA fine-tuning. When transferring from ArXiv to PubMed, the model retained strong generalization capabilities, producing coherent summaries across both scientific and biomedical domains, though slight performance drops were observed due to domain-specific jargon in PubMed. The use of LoRA fine-tuning proved highly beneficial, as it enabled efficient adaptation of PEGASUS with significantly fewer trainable parameters, reducing computational overhead while maintaining competitive performance. Among the strengths, LoRA allowed faster training and avoided catastrophic forgetting, making it suitable for low-resource environments. However, its main weakness lies in limited adaptability for highly domain-specific contexts, where deeper fine-tuning or hybrid approaches may be necessary to capture nuanced knowledge. Overall, the analysis demonstrates that LoRA fine-tuned PEGASUS strikes a balance between efficiency and accuracy, but further improvements are needed for specialized applications.

VI. Conclusion And Future Scope

The study successfully explored abstractive summarization of scientific articles using the PEGASUS model with LoRA-based fine-tuning, demonstrating that parameter-efficient training can achieve high-quality results with reduced computational costs. By evaluating on both ArXiv and PubMed datasets, the model produced coherent and concise summaries, as confirmed by strong ROUGE and BERTScore metrics. The findings highlight that LoRA integration enables effective domain transfer while maintaining training efficiency, positioning it as a viable solution for large-scale summarization tasks.

Despite these achievements, the work also faces certain limitations. The model's performance showed slight degradation when exposed to domain-specific terminology in biomedical texts, indicating that LoRA's low-rank adaptation might not fully capture highly specialized vocabulary. Furthermore, the experiments were constrained by dataset size and computing resources, which limited the exploration of longer input sequences and more advanced decoding techniques. These factors suggest that while the model performs well in general scientific summarization, it may require additional tuning for highly specialized contexts.

Looking ahead, the project can be extended in several promising directions. Training on larger and more diverse datasets would enhance domain generalization and capture nuanced terminology more effectively. Incorporating advanced decoding strategies like nucleus sampling or top-k sampling could improve fluency and reduce redundancy in generated summaries. Additionally, adapting the framework for legal and medical domains holds potential for impactful real-world applications, especially in decision support systems and research assistants. Finally, integrating the system into practical deployment platforms would bridge the gap between research and end-user accessibility, establishing it as an effective approach for condensing large collections of complex documents.

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