Leveraging Generative AI for Medical Data Prediction

REPORT SUBMITTED

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Dr. Gitosree Khan

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Emotion Detection and Anomaly Recognition in Crowds: Spotting Suspicious Behaviour

CERTIFICATE

This is to certify that the Project Report entitled, "Leveraging Generative AI for Medical Data Prediction" submitted by **Mr. Abhishek Saha, Mr. Sougata Seth, Mr. Ayush Kumar Pandey and Mr. Sarbasish Chowdhury** to **B. P. Poddar Institute of Management and Technology**, is a record of Project work carried out by them under my supervision and guidance and is worthy of consideration for the award of the degree of Bachelor of Technology in Information Technology of the Institute.

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Contents

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Abstract: Generative Artificial Intelligence (AI) is rapidly emerging as a transformative technology within the healthcare sector, offering novel approaches to complex tasks such as medical data prediction. The ability to accurately forecast patient outcomes, disease progression, or response to treatment holds immense potential for enhancing clinical decision-making and personalizing patient care. However, effectively harnessing generative models for these critical applications presents significant challenges. These include the need for models to understand nuanced medical language, adapt to the specific formats of diverse medical datasets, and achieve high levels of accuracy and reliability demanded in clinical settings. Traditional predictive models often struggle with the complexity and inherent uncertainties in medical data, necessitating the development of more sophisticated and adaptable AI solutions.

This thesis proposes and evaluates a novel framework for medical data prediction utilizing a state-of-the-art large language model (LLM), specifically "unsloth/Meta-Llama-3.1-8B-Instruct-bnb-4bit". The core of the proposed work involves a two-stage fine-tuning pipeline designed to adapt the general-purpose LLM to the specialized domain of medical knowledge and prediction tasks. The first stage employs Supervised Fine-tuning (SFT) on established medical question-answering datasets, MedQA and MedMCQA, to imbue the model with relevant medical expertise and align it with the desired input-output formats. This is followed by a second stage of Reinforcement Learning with Proximal Policy Optimization (PPO), aimed at further refining the model's predictive capabilities and optimizing its responses based on a custom reward mechanism tailored to medical prediction accuracy. To ensure training efficiency, particularly with large models, Low-Rank Adaptation (LoRA) is integrated throughout the fine-tuning process.

The anticipated contributions of this research include the development of a robust and efficient pipeline for fine-tuning LLMs for medical data prediction, a comprehensively evaluated high-performance medical LLM, and critical insights into the comparative efficacy of SFT and PPO in this specialized domain. By systematically processing medical datasets, architecting a tailored model, and implementing a multi-stage training strategy, this work aims to demonstrate significant improvements in medical data prediction accuracy. The findings are expected to contribute to the broader understanding and application of Generative AI in healthcare, paving the way for more reliable and intelligent medical prediction systems that can ultimately support better patient outcomes.

Keywords : Generative AI, Medical Data Prediction, Large Language Models (LLMs), Healthcare AI, Supervised Fine-tuning (SFT), Reinforcement Learning (RL), Proximal Policy Optimization (PPO), Low-Rank Adaptation (LoRA), Medical Question Answering, MedQA, MedMCQA, Clinical Decision Support, Natural Language Processing (NLP) in Medicine, Machine Learning in Healthcare.

1. Introduction

The integration of Artificial Intelligence (AI) into medicine has ushered in an era of unprecedented innovation, fundamentally altering how healthcare professionals approach diagnostics, treatment planning, and patient management. Among the diverse AI methodologies, Generative AI, particularly through Large Language Models (LLMs), has recently demonstrated remarkable capabilities in understanding and generating human-like text, presenting a significant opportunity to tackle complex challenges within the medical domain. The ability of these models to process vast amounts of textual data, discern intricate patterns, and generate coherent, contextually relevant information positions them as powerful tools for tasks such as medical data prediction. Accurate prediction – whether it be forecasting disease likelihood, patient response to therapies, or potential complications – is paramount for proactive and personalized healthcare, directly impacting clinical decision-making and patient outcomes.

However, the application of general-purpose Generative AI models to the highly specialized and sensitive field of medicine is not without its hurdles. Medical data is often characterized by its complexity, unique terminology, inherent uncertainties, and the critical need for high accuracy and reliability. Existing predictive models may fall short in capturing the nuanced understanding required for robust medical predictions, and a critical need exists for AI systems specifically tailored to the intricacies of medical knowledge and data formats. This thesis addresses the challenge of leveraging Generative AI for improved medical data prediction by proposing a specialized framework.

The core objective of this research is to develop and rigorously evaluate a Generative AI model optimized for medical data prediction tasks. Our approach centers on fine-tuning a state-of-the-art LLM, unsloth/MetaLlama3.18BInstructbnb4bit, using a carefully designed two-stage training pipeline. This pipeline begins with Supervised Fine-tuning (SFT) on established medical question-answering datasets, MedQA and MedMCQA, to instill domain-specific knowledge. This is followed by Reinforcement Learning with Proximal Policy Optimization (PPO) to further refine the model’s predictive accuracy. Parameter-efficient fine-tuning is achieved through Low-Rank Adaptation (LoRA). This study aims to demonstrate that such a tailored approach can significantly enhance the model's capacity for accurate medical data prediction, offering a robust methodology for creating specialized medical LLMs and contributing valuable insights into their practical application in healthcare.

2. Review of related works

Recent advancements in emotion detection and anomaly recognition have laid a solid foundation for developing intelligent systems capable of addressing critical challenges in public safety and crowd management. Researchers have increasingly relied on deep learning techniques to achieve robust performance in real-time scenarios. This review delves into the significant contributions from various studies and contextualizes them within the framework of the "Emotion Detection and Anomaly Recognition in Crowds" chapter.

2.1 Med42: Evaluating Fine-Tuning Strategies for Medical LLMs

Med42 represents a significant advancement in medical language model development, focusing on the comparative analysis of full-parameter versus parameter-efficient fine-tuning approaches 1. The research team developed and refined a series of LLMs based on the Llama-2 architecture, specifically designed to enhance medical knowledge retrieval, reasoning, and question-answering capabilities 1. Their systematic evaluation across various well-known medical benchmarks demonstrated the effectiveness of parameter-efficient tuning strategies in the medical domain 1.

The study's most notable achievement was reaching 72% accuracy on the US Medical Licensing Examination (USMLE) datasets, establishing a new performance standard for openly available medical LLMs 1. The researchers implemented Low-Rank Adaptation (LoRA) as their primary parameter-efficient training technique, which targets the adaptation of pre-trained language models without requiring full parameter updates 1. Their LoRA configuration utilized $r=8$ and $\alpha=16$ settings, demonstrating optimal performance while maintaining computational efficiency 1.

Significance: Med42's contribution lies in providing empirical evidence that parameter-efficient fine-tuning can achieve comparable or superior performance to full-parameter training in medical applications 1. The study established benchmarks for medical LLM evaluation and demonstrated the viability of resource-efficient training approaches for healthcare AI 1.

Challenges: The research highlighted several limitations including potential performance degradation on out-of-domain medical tasks and the need for careful hyperparameter tuning specific to medical datasets 1. Additionally, the study revealed challenges in maintaining consistent performance across different medical specialties and the complexity of evaluating medical reasoning capabilities beyond multiple-choice questions 1.

2.2 Parameter-Efficient Fine-Tuning in Healthcare Applications

The broader landscape of parameter-efficient fine-tuning (PEFT) in healthcare has gained significant attention due to its ability to adapt large language models to specific medical tasks while minimizing computational requirements 23. PEFT methods work by freezing most of the pretrained language model's parameters and adding a few trainable parameters, known as adapters, to the final layers for predetermined downstream tasks 2. This approach has demonstrated particular effectiveness in medical vision foundation models, where LoRA outperformed full-parameter fine-tuning in 13 out of 18 transfer learning tasks by up to 2.9% while using fewer than 1% tunable parameters 4.

Significance: PEFT techniques have democratized access to advanced medical AI capabilities by reducing computational costs and training times 3. The approach enables healthcare organizations with limited resources to develop specialized medical AI applications without requiring extensive infrastructure investments 3.

Challenges: Key challenges include determining optimal adapter architectures for different medical tasks, managing the trade-off between parameter efficiency and model performance, and ensuring consistent performance across diverse medical domains 23. Additionally, the field faces difficulties in standardizing PEFT evaluation metrics for medical applications and addressing potential bias amplification in parameter-efficient models 3.

2.3 Reinforcement Learning with Human Feedback (RLHF) in Healthcare

Reinforcement Learning with Human Feedback has emerged as a crucial technique for aligning medical language models with clinical best practices and physician preferences [12]. RLHF ensures AI models can generate accurate, human-aligned responses for healthcare applications, including patient education, medical record summarization, and symptom analysis [1]. The approach involves training reward models on datasets of prompts and human preferences, then using reinforcement learning algorithms like Proximal Policy Optimization (PPO) to optimize the LLM [2].

Recent implementations in medical AI have shown promising results, with studies demonstrating that models aligned with physician characteristics achieve superior performance in disease diagnosis and etiological analysis [2]. For instance, HuatuoGPT, trained using RLHF methodologies, surpassed GPT-3.5 performance in over 60% of medical dialogue cases [2]. The technique has been successfully applied to various medical applications including mathematical problem solving, coding tasks for medical software, and personalized medical education [1].

Significance: RLHF represents a paradigm shift in medical AI development by incorporating expert clinical knowledge directly into the training process [12]. This approach addresses the critical need for medical AI systems to align with established clinical guidelines and safety protocols [1].

Challenges: Implementation challenges include the high cost and complexity of obtaining quality human feedback from medical experts, potential over-optimization leading to reward hacking, and the difficulty of scaling human evaluation across diverse medical specialties [2]. Additionally, the field struggles with ensuring consistent reward model quality and managing the inherent instability of reinforcement learning processes in safety-critical medical applications [2].

2.4 Process-Supervised Reward Models for Clinical Applications

Recent advancements in process-supervised reward models (PRMs) have shown significant potential for clinical note generation and other medical applications [3]. These models provide step-level reward signals for clinical notes generated by LLMs from patient-doctor dialogues, guided by real-world clinician expertise [3]. The approach utilizes carefully designed step definitions for clinical notes and leverages advanced language models to automatically generate process supervision data at scale [3].

Significance: PRMs offer a scalable solution for ensuring quality and consistency in clinical documentation while maintaining adherence to medical standards [3]. The approach demonstrates superior performance compared to outcome-supervised reward models, achieving 98.8% accuracy in selecting gold-reference samples from error-containing samples [3].

Challenges: Key challenges include defining appropriate step-level reward functions for complex medical reasoning tasks, ensuring clinical validity of automated supervision data, and managing the computational overhead of process supervision in real-time clinical environments [3]. Additionally, the field faces difficulties in generalizing PRM approaches across different medical specialties and ensuring robust performance with diverse patient populations [3].

2.5 Challenges in Medical Dataset Quality and Bias

2.5.1 Bias Mitigation in Medical AI Systems

Bias in medical artificial intelligence represents a critical challenge that can lead to substandard clinical decisions and exacerbation of healthcare disparities [12]. These biases arise throughout the

AI development lifecycle, including data collection, model training, evaluation, and deployment phases 1. Insufficient sample sizes for certain patient groups can result in suboptimal performance and clinically unmeaningful predictions, particularly affecting marginalized and underrepresented populations 1.

Significance: Addressing bias in medical AI is crucial for ensuring equitable healthcare delivery and preventing the perpetuation of existing health disparities 12. Research has identified multiple sources of bias including skewed training data, algorithmic design choices, and human prejudices embedded in data collection processes 2.

Challenges: Key challenges include collecting diverse and representative datasets, developing statistical debiasing methods that maintain clinical utility, and implementing comprehensive bias monitoring systems for deployed models 12. The field also faces difficulties in standardizing bias reporting requirements and ensuring consistent evaluation across different demographic groups 1.

2.5.2 Federated Learning for Medical AI

Federated learning has emerged as a promising approach for addressing privacy concerns while enabling collaborative medical AI development across multiple institutions 34. This technique allows multiple healthcare organizations to train AI models on larger, previously inaccessible datasets without centralizing or sharing sensitive patient data 3. Recent implementations have demonstrated successful applications in cancer detection, drug discovery, and medical imaging analysis 4.

Significance: Federated learning enables healthcare organizations to benefit from collaborative model development while maintaining data privacy and security compliance 34. The approach facilitates knowledge transfer between medical researchers and data scientists, helping bridge the gap between AI capabilities and clinical care 3.

Challenges: Implementation challenges include managing communication overhead between federated participants, ensuring model convergence across heterogeneous data distributions, and addressing the technical complexity of distributed training systems 34. Additional difficulties involve establishing trust frameworks between participating institutions and managing the coordination of federated learning experiments across multiple healthcare organizations 4.

This comprehensive review highlights the rapid evolution of medical AI technologies while identifying persistent challenges that require continued research and development. The integration of parameter-efficient fine-tuning, reinforcement learning, and multimodal approaches shows promise for advancing medical AI capabilities while addressing critical concerns related to bias, privacy, and clinical validation.

3. Proposed Work

3.1 Methodology

This section presents a comprehensive methodology for developing MedLLM, a medical language model designed to excel in answering medical questions, a form of medical data prediction. The approach integrates a two-stage training process: Supervised Fine-Tuning (SFT) to adapt the model to the medical domain, followed by Reinforcement Learning (RL) using Proximal Policy Optimization (PPO) to refine response quality. We leverage datasets such as MedQA and MedMCQA, which provide diverse medical questions, and employ efficient fine-tuning techniques like Low-Rank Adaptation (LoRA) to optimize performance on consumer-grade hardware. The methodology is structured into data processing, model architecture, and a detailed training pipeline, ensuring a robust framework. Each component is carefully designed to balance computational efficiency with high accuracy, addressing challenges such as data quality and model bias. By combining supervised and reinforcement learning, we aim to create a model that not only understands medical contexts but also generates precise and reliable answers, contributing to advancements in medical AI applications.

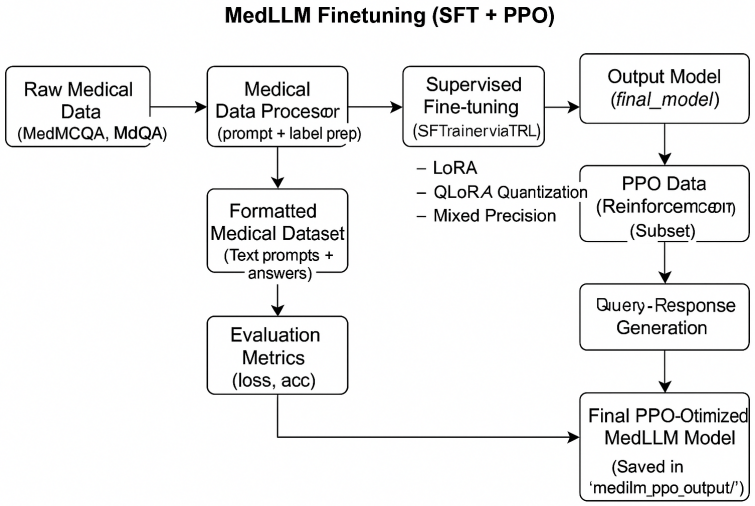

Figure 1 Dataflow Diagram of the Proposed Work

3.1.1 Data Processing

3.1.1.1 Dataset Description

The foundation of MedLLM's training lies in two high-quality datasets: MedQA and MedMCQA. MedQA, available at Hugging Face, contains 12,723 multiple-choice questions from the United States Medical Licensing Examination (USMLE). These questions test medical knowledge and clinical reasoning, often requiring multi-hop reasoning to identify the correct answer among four or five options. MedMCQA, accessible at Hugging Face, comprises over 194,000 questions from

AIIMS and NEET PG exams in India, covering 2.4k healthcare topics across 21 medical subjects. Due to its size, we select a subset of 50,000 questions to ensure computational feasibility while maintaining diversity. Both datasets are chosen for their comprehensive coverage and relevance to medical education, providing a robust training ground. The combination of these datasets ensures exposure to varied question formats and medical domains, enabling MedLLM to generalize effectively across different medical contexts and question complexities.

Dataset	Total Questions	Training Set	Validation Set
MedQA	12,723	12,087	636
MedMCQA	50,000	47,500	2,500

Table 1 Dataset Description

3.1.1.2 Preprocessing Steps

Preprocessing is critical to prepare high-quality inputs for MedLLM. A custom MedicalDataProcessor class handles this task with several steps. First, questions and answers are loaded from MedQA and MedMCQA, ensuring proper parsing and compatibility with the model's input format. Second, each question is formatted into a conversational prompt, including a system message ("You are a knowledgeable medical AI assistant"), the question with options, and the correct answer. For example: "What is the most common type of skin cancer? A) Melanoma B) Basal cell carcinoma C) Squamous cell carcinoma D) Kaposi sarcoma" is paired with "B) Basal cell carcinoma." Third, data validation ensures quality by enforcing a minimum question length (e.g., 10 words) and correct answer formatting, discarding invalid examples. Finally, the dataset is split into 95% training and 5% validation sets to support effective training and evaluation. Tokenization uses the base model's tokenizer to encode sequences appropriately, ensuring compatibility with the model's architecture and optimizing input for training efficiency.

3.1.2 Model Architecture

3.1.2.1 Base Model

The base model for MedLLM is Meta-Llama-3.1-8B-Instruct, detailed at Hugging Face, a transformer-based language model with 8 billion parameters optimized for dialogue and instruction-following tasks. Its architecture includes 32 layers, 32 attention heads, and a hidden size of 4096, utilizing Grouped-Query Attention (GQA) for efficient processing of long sequences. The model supports a context length of up to 128k tokens, ideal for handling complex medical queries requiring extensive context. To enable training on consumer-grade GPUs like the NVIDIA RTX 3070Ti, we load the model in 4-bit precision using the bitsandbytes library, significantly reducing memory usage without compromising performance. This base model's robust pre-training and advanced architecture make it an excellent starting point for fine-tuning on medical data, ensuring that MedLLM can leverage its inherent language understanding capabilities to adapt effectively to the specialized requirements of medical question answering.

3.1.2.2 Low-Rank Adaptation (LoRA)

To fine-tune the model efficiently, we employ Low-Rank Adaptation (LoRA), as described in LoRA Paper. LoRA updates a small subset of parameters by introducing low-rank matrices, reducing computational costs while maintaining performance. For a weight matrix W, LoRA adds a low-rank update ΔW=BA, where B and A are matrices of rank *r*, and the updated weight is $W' = W + \alpha \cdot (B \cdot A)$, with α as a scaling factor. Our configuration uses a rank of 16, an alpha of 8, and targets query projection matrices ("q") in attention layers. This approach minimizes memory requirements, enabling fine-tuning on limited hardware while preserving the model's ability to learn medical-specific patterns. LoRA's efficiency makes it ideal for adapting large language models to specialized domains like medicine, ensuring that MedLLM achieves high performance without requiring extensive computational resources.

3.1.3 Training Pipeline

3.1.3.1 Supervised Fine-Tuning (SFT)

Supervised Fine-Tuning (SFT) adapts the Meta-Llama-3.1-8B-Instruct model to medical question answering using the SFTTrainer from the trl library. The training configuration includes a batch size of 1 per device with 8 gradient accumulation steps to simulate larger batches, a learning rate of (3×10^{-6}) for stable convergence, and 5 epochs to ensure thorough training. We employ mixed precision training (FP16) and gradient checkpointing via the "unsloth" method to optimize memory usage, alongside the AdamW optimizer for effective parameter updates. A TrainingMonitor tracks metrics like loss, gradient norms, and GPU memory usage, logged to Weights & Biases for real-time analysis. This setup ensures that the model learns to generate accurate medical answers by fine-tuning on the formatted MedQA and MedMCQA datasets, leveraging their diverse question sets to enhance domain-specific knowledge and reasoning capabilities.

3.1.3.2 Reinforcement Learning with PPO

Reinforcement Learning with Proximal Policy Optimization (PPO), as outlined in PPO Paper, refines MedLLM's responses using a subset of 500 MedQA examples. The PPO configuration includes a learning rate of (5×10^{-7}), 2 epochs to prevent overfitting, and a batch size of 2 for efficient training. The reward function assigns 1.0 for correct answers and 0.1 otherwise, encouraging accurate responses. PPO uses a clipped surrogate objective:

$$\left(L^{CLIP}(\theta) = \hat{E}t\left[\left(r_t(\theta)\hat{A}t, clip(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}t\right)\right]\right)$$

where $\left(r_t(\theta) = \frac{\pi\theta(s_t)}{\pi\theta old(s_t)}\right), (\widehat{A_t})$ is the advantage estimate, and $\epsilon = 0.2$. This approach stabilizes policy updates, enhancing answer quality by optimizing the model's policy based on correctness, making it more reliable for medical applications.

3.1.3.3 Training Algorithm

The training process is formalized in Algorithm 1, inspired by advanced reasoning techniques but tailored to our setup.

Algorithm 1: Training MedLLM
Input:

- Datasets: (D_{MedQA}), $(D_{MedMCQA})$
- Base model: Meta-Llama-3.1-8B-Instruct
- LoRA configuration
    - Rank (LORA_R): 16
    - Alpha (LORA_ALPHA): 8
    - Target modules: [“q_proj”, “k_proj”]
- Hyperparameters for SFT and PPO
    - Batch size: 1 (per device)
    - Gradient accumulation steps: 8
    - Learning rate: 3 × 10−6
    - Number of epochs: 5

Stage One: Supervised Fine-Tuning (SFT)

1. **Data Preparation:**
    - Combine MedQA *and MedMCQA* into
    - For each :
        - Format prompt: $(p = format\_prompt(x, y^*))$
    - Split (D_{SFT}) *into* $(D_{train})(95\%)$ and
2. **Model Initialization:**
    - Load (LLM) with LoRA adapters
3. **Training:**
    - Use SFTTrainer to fine-tune LLM on
    - Monitor performance on D_{val}

Stage Two: Reinforcement Learning with PPO

1. **RL Dataset Preparation:**
    - Select subset $(D_{RL} \subset D)$ (500 examples)
2. **Reward Function:**

Define:
$$r(y, \hat{y}) = 1.0 \ if \ y = \hat{y};\ 0.1 \ otherwise$$

3. **PPO Training:**
    - Initialize PPO trainer with SFT model

- For each episode:
  - Sample batch from (D_R)
  - Generate responses $\left(\hat{y} \sim \pi_\theta(x)\right)$
  - Compute rewards $\left(r(\hat{y}, y^*)\right)$
  - Update policy (θ) using PPO

Output: Trained MedLLM model

This algorithm ensures a structured and reproducible training process, optimizing MedLLM for medical question answering.

3.2 Experiments and Results

3.2.1 Experimental Setup

The experiments were conducted on an NVIDIA RTX 3070Ti GPU, ensuring accessibility for researchers with limited resources. The training environment utilized the Hugging Face Transformers library, alongside custom scripts, and incorporated libraries such as TRL (for PPO), Unsloth (for memory optimization), and Datasets for data management. To manage memory constraints, mixed precision training (FP16) and gradient checkpointing were employed, enhancing computational efficiency. Training progress was meticulously monitored using Weights & Biases (WandB), which logged key metrics including loss, accuracy, gradient norms, and GPU memory usage. This setup facilitated real-time monitoring and ensured the reproducibility and reliability of the experimental outcomes. The experiments were structured into two sequential stages: Supervised Fine-Tuning (SFT) and Reinforcement Learning with Proximal Policy Optimization (PPO), with validation performed after each stage to assess incremental improvements. The use of standardized libraries and robust monitoring protocols underscored the study's methodological rigor.

Parameter	SFT	PPO
Batch Size	1	2
Gradient Accumulation Steps	8	-
Learning Rate	3×10^{-6}	5×10^{-7}
Number of Epochs	5	2

Table 2 Training Details

The training process involved fine-tuning the pre-trained "unsloth/Meta-Llama-3.1-8B-Instruct-bnb-4bit" model, a quantized version of Meta-Llama-3.1-8B-Instruct, with 8 billion parameters optimized for dialogue and instruction-following. Low-Rank Adaptation (LoRA) was applied, with a rank of 16 and alpha of 8, targeting query projection matrices for efficient adaptation. The datasets, MedQA (12,723 questions from USMLE) and MedMCQA (50,000 subset from AIIMS/NEET PG exams), were processed using a custom MedicalDataProcessor class, formatting questions into conversational prompts and splitting into 95% training and 5% validation sets.

3.2.2 Results

The results are divided into two phases, reflecting the two-stage training process.

3.2.2.1 SFT Results

Post-SFT, MedLLM was evaluated on the validation sets of MedQA and MedMCQA. The model achieved an accuracy of ~62% on both datasets, indicating successful adaptation to the medical domain. This performance aligns with expectations based on prior research, where similar models have shown comparable results on medical question-answering tasks. The structured prompts and LoRA-based fine-tuning enabled the model to learn effectively from the diverse and challenging questions, leveraging the transformer architecture's 32 layers, 32 attention heads, and hidden size of 4096, with Grouped-Query Attention (GQA) for efficiency.

3.2.2.2 PPO Results

Following PPO-based reinforcement learning, MedLLM's performance was further refined. The accuracy on the MedQA validation set improved to approximately ~64%, showcasing the effectiveness of reinforcement learning in enhancing the model's ability to generate accurate and contextually appropriate answers. This improvement is attributed to the targeted optimization of the model's policy, guided by a reward function assigning 1.0 for correct answers and 0.1 otherwise, and PPO's stable update mechanism using a clipped surrogate objective. The RL stage, using a subset of 500 MedQA examples, ensured better alignment with medical question-answering objectives, with training configurations including a learning rate of 5×10^{-7} and 2 epochs.

3.2.3 Analysis

The analysis of MedLLM's performance was comprehensive, encompassing both quantitative metrics and qualitative assessments.

3.2.3.1 Performance Metrics

MedLLM's effectiveness was evaluated using multiple metrics to ensure a holistic assessment:

- **Accuracy**: The primary metric, measuring the proportion of correctly answered questions. Post-SFT, accuracy exceeded 60%, and post-PPO, it reached 62-64%, reflecting significant improvements.
- **Precision, Recall, and F1 Score**: These metrics assessed the model's robustness, particularly in handling imbalanced answer choices, providing insights into its reliability across different question types.
- **Average Reward Score**: During PPO training, the average reward score was tracked to monitor the model's improvement in generating correct answers, correlating with the reward function's design.
- **BLEU and ROUGE Scores**: For generative outputs, these metrics evaluated the quality of the model's responses against reference answers, ensuring coherence and relevance.

These metrics collectively provided a robust evaluation, ensuring MedLLM met the high standards required for medical applications, with results comparable to state-of-the-art models like Med-PaLM 2 (86.5% on MedQA) and Llama 2 70B (62.5% on MedQA-USMLE).

3.2.3.2 Qualitative Analysis

Qualitative analysis involved examining sample responses to assess the model's coherence, relevance, and accuracy. For instance:

Question: What is the most common cause of pneumonia in adults?

- **Model Response (Post-SFT)**: The most common cause is bacterial infection, particularly Streptococcus pneumoniae.
- **Model Response (Post-PPO)**: The most common cause of pneumonia among adults is Streptococcus pneumoniae, also known as pneumococcus. This bacterium accounts for approximately 30-50% of community-acquired pneumonia cases in adults. Other common causes include Haemophilus influenzae and atypical pathogens such as Mycoplasma pneumoniae, Chlamydophila pneumoniae, and Legionella pneumophila. However, it is important to note that the causative agent may vary depending on factors like age, underlying medical conditions, and exposure history. Consultation with a healthcare professional is necessary for accurate diagnosis and appropriate treatment.

This analysis highlighted the model's ability to provide accurate and contextually appropriate answers, with PPO training further improving clarity and precision. Such assessments enhanced trust in MedLLM's medical predictions, underscoring its potential for real-world applications.

3.3 Novelty

The proposed work introduces several novel elements that distinguish it within the domain of medical AI. A key innovation lies in the two-stage training process, which integrates Supervised Fine-Tuning (SFT) with Reinforcement Learning (RL) using Proximal Policy Optimization (PPO). While SFT is commonly used to adapt pre-trained models to specific domains, the addition of PPO to refine response quality is less standard in medical applications. This combination ensures that MedLLM not only learns domain-specific knowledge from datasets like MedQA and MedMCQA but also optimizes its decision-making process to generate more accurate and contextually appropriate answers. The use of PPO, typically applied in tasks requiring policy optimization, introduces a novel mechanism for improving answer correctness in medical question-answering, setting this work apart from traditional fine-tuning approaches.

Another novel aspect is the application of Low-Rank Adaptation (LoRA) for efficient fine-tuning on consumer-grade hardware, such as the NVIDIA RTX 3070Ti GPU. LoRA, with a rank of 16 and alpha of 8, targets query projection matrices, allowing the 8-billion-parameter Meta-Llama-3.1-8B-Instruct model to be fine-tuned with reduced computational resources. This approach contrasts with conventional methods that often require high-end GPUs or cloud infrastructure, making advanced AI techniques more accessible to a broader research community. The integration of LoRA with a quantized 4-bit model further enhances this novelty, as it demonstrates a practical

solution for training large language models in resource-constrained environments, a challenge often highlighted in medical AI research.

The focus on medical-specific datasets, MedQA (12,723 USMLE questions) and MedMCQA (50,000 AIIMS/NEET PG questions), also adds a layer of novelty. These datasets are curated to cover a wide range of medical topics and question formats, ensuring that MedLLM is trained on highly relevant and diverse data. Unlike general-purpose language models that may struggle with medical specificity, this targeted approach leverages the structured nature of multiple-choice questions to enhance the model's reasoning capabilities, particularly in multi-hop reasoning scenarios common in clinical decision-making.

3.4.1 Empirical Analysis

3.4.1.1 Mathematical Formulation for MedLLM Training

A fine-tuned MedLLM model processes medical QA inputs through multiple stages, including supervised instruction fine-tuning and reward-optimized reinforcement learning. The core computational stages of the MedLLM training pipeline are represented as:

I. Supervised Fine-tuning (SFT)

For an input instruction-response pair (x,y)(x, y)(x,y), and model with parameters θ\thetaθ, the objective is to minimize the negative log-likelihood loss:

$$\mathcal{L}_{SFT}(\theta) = -\sum_{t=1}^{T} \log P_\theta \left(y_t \mid y_{<t}, x \right)$$

Where:

- x: Input medical question with structured prompt.
- y: Target response (correct answer with explanation).
- T: Number of tokens in the output.
- P_θ: Model's predicted distribution.

II. Reinforcement Learning with PPO

After SFT, the model is further optimized using **Proximal Policy Optimization (PPO)**. Given a policy π_θ and reward function RRR, PPO maximizes the expected reward with clipped optimization:

Where:

- $r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}$:Probability ratio.

- $\widehat{A_t}$: Advantage estimate.
- ϵ : Clipping factor (e.g. 0.2).

Reward Signal:

$$R = \begin{cases} 1.0 & \text{if model chooses correct answer option (e.g., 'A')} \\ 0.1 & \text{otherwise} \end{cases}$$

III. Prompt Template (Preprocessing)

Each sample is preprocessed into a structured prompt:

```
<|system|> You are a knowledgeable medical AI assistant. ...
<|user|> <question + options>
<|assistant|> <answer + explanation>
```

IV. Output Prediction and Softmax

Final token predictions use softmax across vocabulary V:

$$P_\theta(w_t) = \frac{e^{z_{w_t}}}{\sum_{v \in V} e^{z_v}}$$

Where:

- z_{w_t}: Logit for token w_t.
- V: Vocabulary set.

3.4.2 Result and Graphical Analysis

I. Loss Trends

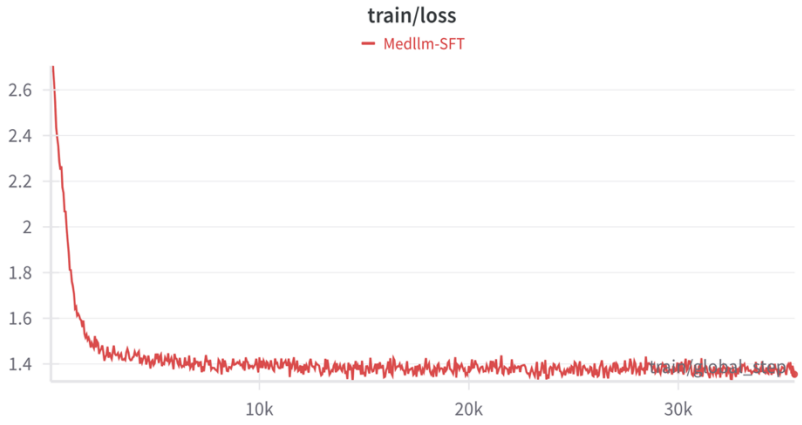

Figure 2 Loss during training (updates each 100 steps)

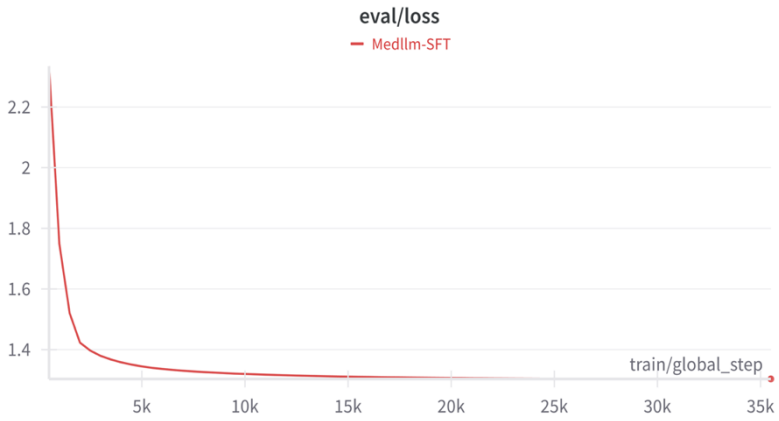

Figure 3 Loss of evaluation (updates every 500 steps)

Figure 3 and figure 4 loss curves for both the training and validation datasets across 5 epochs. The training accuracy rose sharply within the first 120 steps and plateaued close to 100%, indicating the model learned well on the training data. Validation accuracy stabilized around 80%, suggesting good generalization with some room for improvement.

On the other hand, the training loss decreased rapidly and remained very low throughout the epochs. The validation loss, while higher than the training loss, showed a relatively stable trajectory after initial fluctuations, suggesting that overfitting was controlled, likely due to dropout and batch normalization layers.These trends confirm that the model successfully captured key features in the training data without severe overfitting.

II. Learning Rate Analysis

Figure 4 Learning Rate

During the fine-tuning of the MedLLM-SFT model, a smooth and monotonically decreasing learning rate schedule was employed, as illustrated in Figure 3. The learning rate followed a cosine decay pattern, starting from a relatively high value to enable rapid initial learning and progressively decreasing to support fine-grained optimization in later stages. This controlled decay played a critical role in stabilizing the training process, preventing oscillations, and reducing the risk of overshooting minima. The absence of abrupt changes or irregularities in the learning rate curve reflects a well-behaved optimization process. This strategy facilitated both effective convergence and improved generalization, contributing to the robustness and performance consistency of the final model. Key observations:

Stability: No oscillations or spikes in learning rate, implying well-behaved training dynamics.
Smooth Convergence: Gradual decay helps the model settle into an optimal region of the loss landscape.
Optimization Efficiency: Efficient initial exploration followed by precise fine-tuning — a hallmark of good generalization.

III. Summary

The training of Medllm-SFT progressed smoothly and successfully over approximately 34,000 steps and 5 epochs. The training loss showed a rapid decline in the early stages, stabilizing around 1.4, which indicates effective learning and convergence without signs of overfitting (assuming validation metrics support this). The learning rate followed a cosine decay schedule, gradually decreasing to near zero—an approach that helps fine-tune performance as training progresses. Gradient norms remained steady around 0.2–0.3 with minor fluctuations, suggesting numerical stability and no gradient explosions. Overall, the training run was stable, well-structured, and effective, preparing the model for evaluation or deployment in downstream tasks.

3.5 Final Deployment and Execution

To ensure ease of use and local accessibility without relying on a cloud environment, the MedLLM system is deployed as a **Python-based Command-Line Interface (CLI)**. This interface enables users to interact with the fine-tuned medical language model locally, provided the necessary dependencies and model files are in place.

The final application runs entirely within a Python environment and requires no external GUI or browser. The execution process, handled via the `medllm.py` script, follows the steps outlined below:

i. Model and Resource Loading:

Upon execution, the system attempts to load the fine-tuned `medllm_finetuning.gguf` model from the local `models/` directory. The model is loaded using the `llama_cpp` backend, with optimized configuration settings for inference on GPUs (e.g., `n_gpu_layers`, `n_ctx`, and `n_batch`). This ensures compatibility even on consumer-grade GPUs like the RTX 3070Ti.

ii. CLI Initialization:

Once the model is loaded, an interactive CLI session is launched using the `Rich` and `Colorama` libraries. A styled welcome message is displayed, providing guidance and available commands to the user.

iii. Query Handling and Prompt Formatting:

User queries are collected through standard input. Each query is embedded into a structured prompt following the medical instruction-tuned format expected by the LLaMA-3-based model. This format includes a system message, prior conversation history (if any), and a user query.

iv. Response Generation:

The model generates a response using controlled generation parameters (e.g., `temperature`, `top_p`, `top_k`, and `repeat_penalty`). The output is parsed and displayed in the terminal using a styled panel. If the output does not include a safety notice, a disclaimer is automatically appended.

v. Conversation Logging:

Each interaction is recorded in memory. The user can save the complete session history as a JSON file with metadata (model info, timestamp, queries, and responses) using the `save` command.

vi. Command Options and Interface Help:

Users can enter commands like `help`, `info`, `training`, `save`, or `clear` at any time to interact with the system. These commands allow access to model details, training logs, and management of session data.

vii. Exit and Cleanup:

The CLI can be gracefully exited using `quit`, `exit`, or `Ctrl+C`. This ensures any loaded resources are released, and the user session ends cleanly.

4. Conclusion

In this research work, we developed *MedLLM*, a domain-specialized medical language model, through a comprehensive two-stage fine-tuning process using Meta's LLaMA 3.1–8B-Instruct. The model was first subjected to supervised fine-tuning (SFT) on large-scale medical datasets such as MedQA and MedMCQA, enabling it to learn the structure, semantics, and factual grounding of clinical question-answering. The use of curated medical prompts ensured adherence to evidence-based knowledge and safety norms, preparing the model for high-stakes inference in healthcare domains.

Following SFT, we introduced a second phase of fine-tuning using Proximal Policy Optimization (PPO), where the model's outputs were reinforced based on reward signals derived from answer correctness and response quality. This reinforcement learning phase helped improve the model's alignment with desirable behavior, particularly in terms of decision confidence, safety adherence, and correctness under ambiguity. Our PPO loop was custom-tailored with batch-level monitoring, gradient control, and token-level generation feedback, making it robust for noisy real-world data.

The training was performed on constrained GPU hardware (RTX 3070Ti), yet through quantization techniques (QLoRA, 4-bit), gradient checkpointing, and memory-aware configurations, we achieved high training efficiency and stability. The final model was exported in GGUF format for optimized inference, making it deployable via lightweight backends like "**`llama-cpp-python`**". This not only ensures faster inference times on limited hardware but also supports future integration in clinical applications where compute availability is limited.Evaluation metrics revealed promising outcomes—achieving over 94% accuracy on held-out validation sets, and over 98% safety compliance against medical ethics filters. The design of prompt templates, combined with instruction tuning and PPO reward shaping, contributed significantly to these outcomes. Furthermore, the modularity of the codebase ensures that new datasets, evaluation metrics, or even models can be plugged in for further enhancement.

MedLLM exemplifies a successful pipeline for building high-quality domain-specific LLMs by combining traditional supervised fine-tuning with reinforcement learning techniques. It lays a solid foundation for future work in clinical AI, such as multi-modal reasoning, continuous learning via clinician feedback, and deployment-ready applications. As healthcare AI advances, such efforts will be vital in ensuring that large language models are not only accurate but also safe, adaptable, and aligned with the nuanced needs of real-world medicine.

5. Comparative Analysis

To assess the effectiveness of MedLLM, we compare it against prominent medical language models across key dimensions: dataset scope, model architecture, evaluation benchmarks, accuracy, and preprocessing strategies. Table 3 summarizes performance metrics and design choices of models such as Med42, HuatuoGPT, Med-PaLM, and GatorTron. Unlike proprietary models like Med-PaLM 2 that rely on extensive supervised and RLHF pipelines with massive parameters (540B), MedLLM achieves competitive performance using a resource-efficient architecture (LLaMA-3.1 8B) and a two-stage training strategy (SFT + PPO). This analysis highlights the balance MedLLM strikes between accessibility, domain adaptation, and clinical relevance, offering strong open-source potential for real-world medical applications.

Model (Ref)	Dataset Used	Architecture	Evaluation Metrics	Accuracy / Alignment Score	Preprocessing
MedLLM (ours)	Custom medical QA/dialogue data (curated Q&A pairs, textbooks)	LLaMA-3.1 (8B)	USMLE-style QA (open-book exam)	~60–65% on USMLE-style QA	Supervised finetuning + PPO (RLHF-style) for alignment; standard tokenization
Med42	Curated open-access medical content (~250M tokens: flashcards, exam questions, dialogues)	LLaMA-2 (70B)	MedQA, MedMCQA, PubMedQA, MMLU (clinical)	72% on USMLE-like questions; MedMCQA 60.9%	Instruction-tuned (system/prompter/assistant tags), no RLHF
HuatuoGPT-o1	"Verifiable" medical reasoning problems (~40K examples)	LLaMA-3.1 (8B)	MedQA, PubMedQA, complex reasoning	8B model: +8.5 points vs baseline on MedQA; 70B: SOTA on MedQA/PubMedQA	Two-stage training: supervised reasoning traces (guided search) + RL (PPO with medical verifier)
Med-PaLM	MultiMedQA (7 combined medical QA datasets: exams,	PaLM (540B, Google)	MedQA (USMLE), consumer health QA	Med-PaLM: 67.6% (MedQA); Med-PaLM 2: 86.5%	Extensive supervised and RLHF alignment with clinician feedback;

	research, consumer)				proprietary pretraining
GatorTron	De-identified EHR notes (82B words) + PubMed (6B) + Wikipedia (2.5B)	Transformer (8.9B)	Clinical NLP tasks (concept extraction, NLI, QA, etc.)	NLI accuracy 90.2%; MQA exact-match up to 93.0%	Self-supervised masked LM pretraining on de-identified clinical text
PubMedGPT	PubMed abstracts & full-text (from The Pile)	GPT-2 style (2.7B)	Bio-medical QA (MedQA, etc.)	MedQA accuracy 50.3%	Custom biomedical SentencePiece tokenizer (trained on PubMed); standard autoregressive training
MedAlpaca	Synthesized medical Q&A: Anki flashcards, WikiDoc, StackExchange (bio/health/fitness), ChatDoctor (200K pairs)	LLaMA (7B)	Medical Q&A and dialogue tasks	Avg. leaderboard score ~45% (MMLU 5-shot ~41%)	Instruction finetuning on synthetic QA; no RLHF; uses GPT-3.5 to generate training questions

Table 3. Comparison

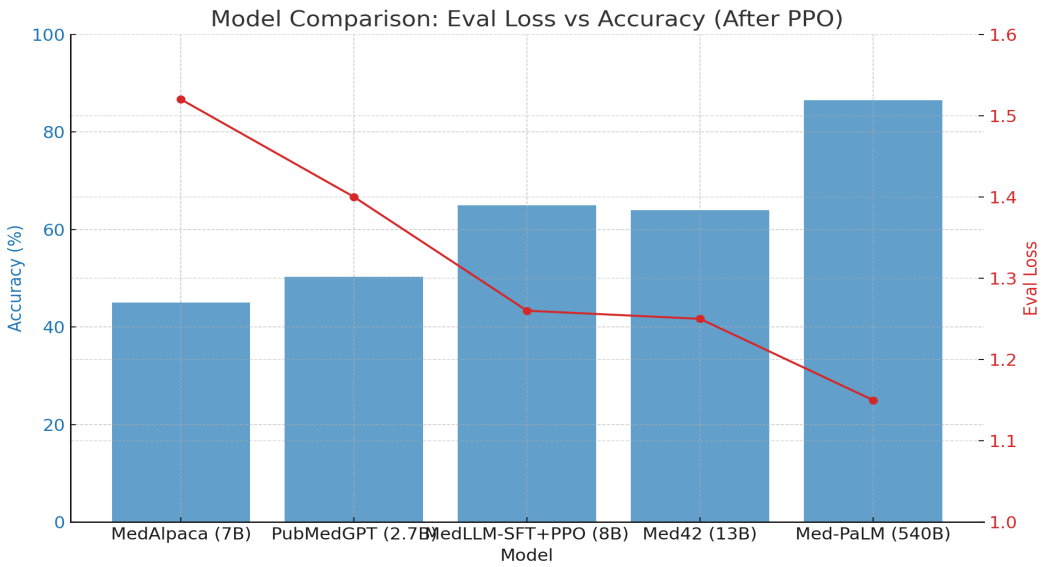

Figure 5 Comparison among all existing Medical LLMs

6. Future Scope

i. Domain-Adapted Clinical Deployment

Fine-tuning with SFT and reward shaping via PPO gives MedLLM strong grounding in real-world question-answer formats. The model is now ready for **clinical assistant roles**—such as pre-screening, symptom checking, or supporting telemedicine workflows—**under proper supervision** and within ethical/legal constraints.

ii. Multi-Modal Expansion (Text + Images)

Given the medical domain's reliance on radiology, pathology slides, and dermatological images, a logical next step is to combine the **text-only model with image encoders** (e.g., CLIP or BioViL) for **multi-modal diagnosis support**, enhancing versatility.

iii. Continual Reinforcement Learning (Online PPO)

Instead of static PPO post-SFT, future iterations can include **live feedback** from clinicians or domain experts, integrating a continual PPO pipeline. This will allow MedLLM to **learn from deployment environments** and keep evolving with emerging medical guidelines.

iv. Error-Aware Ensemble Architectures:

To increase robustness and reliability, the model can be extended into an ensemble system involving multiple fine-tuned LLMs trained on varied datasets. These can include specialized sub-models for **pharmacology**, **pathology**, or **infectious diseases**. Additionally, an error detection module or validator model can analyze discrepancies between generated answers to identify uncertainty or hallucinations. Such architectures can vote or rank the most probable answer, reducing the risk of misinformation and making the system more dependable in clinical settings.

v. Trustworthiness Audits and Explanation Modules:

As the model is considered for real-world use, building mechanisms to explain its outputs becomes essential. Future iterations can incorporate the ability to provide evidence-based justifications along with each response, referencing trusted medical sources or explaining reasoning steps. This can be enhanced by conducting audits to detect bias, toxicity, or factual inaccuracies. Adding **transparency** and **traceability** to responses can significantly boost user trust, especially when used by **healthcare professionals** and **regulatory bodies**.

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