A Fine-Tuned Large Language Model for Empathetic Mental Health Chabot

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***Abstract*—Mental health disorders affect nearly one billion people worldwide, yet access to professional care remains limited due to cost, stigma, and a global shortage of therapists. This paper presents a therapy chatbot designed to deliver empathetic, personalized mental health support through advanced conversational AI. Three large language models (LLMs)—Llama-3.1-8B-Instruct, Qwen/Qwen2-7B-Instruct, and Mistral-7B-Instruct-v0.3—were fine-tuned on a curated 20,000-row subset of an 800,000-row mental health conversation dataset, addressing diverse emotional contexts. The Gemini API evaluated responses across empathy, understanding, advice quality, and conversational flow, with Qwen2-7B-Instruct achieving superior performance. Deployed as a web-based application integrating cognitive-behavioral therapy (CBT) principles, the system underwent rigorous testing with 50 participants, yielding 85% user satisfaction and 90% accuracy in emotion detection. Fine-tuning results demonstrated stable convergence, with Qwen achieving a validation loss of 0.8510. This work underscores the transformative potential of fine-tuned LLMs in providing scalable, accessible mental health support, offering valuable insights into model optimization, evaluation methodologies, and ethical considerations for AI-driven therapeutic interventions.**

***Index Terms*—Chatbot, Mental Health, Large Language Models, Fine-Tuning, Conversational AI, Cognitive-Behavioral Therapy**

I. Introduction

Mental health disorders constitute a pressing global challenge, impacting over 970 million individuals, with depression and anxiety ranking among the leading causes of disability worldwide [1]. The World Health Organization highlights a critical shortage of over 4 million mental health professionals, with low-income countries averaging less than 1 psychiatrist per 100,000 people [1]. Barriers such as exorbitant treatment costs, pervasive social stigma, geographic inaccessibility, and prolonged waiting times for appointments exacerbate this crisis, leaving millions without timely or adequate support. Conversational AI, powered by advanced large language models (LLMs), offers a transformative approach to address these gaps, providing scalable, anonymous, and cost-effective interventions. These systems excel in delivering empathetic, context-aware responses, making them well-suited for supporting individuals with mild to moderate mental health concerns, such as stress, anxiety, and low mood, while serving as a complementary tool to traditional therapeutic practices.

This paper introduces a therapy chatbot developed to enhance access to mental health support through sophisticated natural language processing (NLP). The system leverages fine-tuned LLMs to provide personalized, empathetic interactions, incorporating cognitive-behavioral therapy (CBT) principles to guide users through structured therapeutic techniques. The development process involved fine-tuning three LLMs—Llama-3.1-8B-Instruct, Qwen/Qwen2-7B-Instruct, and Mistral-7B-Instruct-v0.3—on a meticulously curated 20,000-row subset of an 800,000-row mental health conversation dataset. This subset was selected due to the computational limitations of a Google Colab T4 GPU, using stratified sampling to ensure representation of diverse emotional contexts. The fine-tuned models were rigorously evaluated using the Gemini API, which assessed responses based on empathy, understanding, advice quality, and conversational flow. Qwen2-7B-Instruct emerged as the top performer, demonstrating exceptional emotional sensitivity and therapeutic relevance in its responses.

The therapy chatbot was implemented as a web-based application, featuring an intuitive user interface and a hybrid dialogue system that integrates rule-based CBT prompts with dynamic, LLM-generated responses. A comprehensive user study with 50 participants validated the system's efficacy, providing quantitative metrics on user satisfaction and emotion detection accuracy, alongside qualitative insights into user experiences. Fine-tuning results, including detailed training and validation loss trajectories, informed the model selection process, with Qwen2-7B-Instruct achieving a validation loss of 0.8510. The project tackles critical challenges in mental health AI, including computational efficiency, ethical design, and the development of robust evaluation frameworks, contributing to the broader goal of democratizing mental health support.

The objectives of this paper are to: (1) provide a comprehensive account of the system's development, encompassing dataset curation, fine-tuning methodology, system architecture, implementation details, and evaluation protocols, (2) present detailed results from fine-tuning experiments, model comparisons, and user testing, supported by quantitative metrics and qualitative feedback, and (3) discuss the implications of fine-tuned LLMs for scalable mental health interventions, addressing technical, ethical, and societal dimensions. The paper is structured as follows: Section II reviews related work, Section III details methodology, Section IV presents results, Section VI discusses findings, and Section VII concludes with future directions.

II. Related Work

Conversational AI has emerged as a pivotal tool in mental health support, offering scalable solutions to address barriers to traditional therapy. Systems like Woebot and Wysa have established benchmarks in this field. Woebot, rooted in cognitive-behavioral therapy (CBT), delivers structured interventions such as thought challenging, cognitive restructuring, and behavioral activation to mitigate depressive symptoms [2]. Clinical trials have demonstrated its efficacy, with users reporting significant reductions in depression scores after two weeks of engagement [2]. Woebot's rule-based dialogue system ensures consistent delivery of evidence-based techniques, but its reliance on predefined scripts limits its ability to adapt to diverse, free-form user inputs, potentially reducing effectiveness in complex emotional scenarios. Wysa, in contrast, focuses on self-care through mood tracking, mindfulness exercises, and positive psychology interventions [3]. Available on mobile platforms, Wysa supports users in managing stress, anxiety, and low mood, with studies reporting improved emotional resilience and user engagement [3]. However, its structured dialogue flows similarly constrain its capacity to handle nuanced, open-ended conversations, a challenge that LLM-based systems aim to overcome.

The advent of large language models (LLMs) has revolutionized conversational AI, offering unprecedented capabilities in natural language understanding and generation. Models such as BERT [4], GPT [9], and Llama [5] have set new standards in tasks like text classification, sentiment analysis, and dialogue generation. However, their application in mental health requires domain-specific fine-tuning to align with therapeutic objectives, such as empathy, emotional sensitivity, and adherence to evidence-based practices [6]. Research on fine-tuning LLMs for mental health applications demonstrates significant improvements in response quality, with fine-tuned models outperforming general-purpose counterparts in detecting emotional cues (e.g., sadness, anxiety) and generating CBT-aligned responses [7]. Recent advancements in efficient LLMs, such as Qwen and Mistral, have democratized access to high-performance models, enabling their deployment in resource-constrained environments like the T4 GPU used in this study [10]. These models balance computational efficiency with conversational prowess, making them ideal for specialized applications.

Fine-tuning techniques have evolved to address the computational challenges of adapting large models. Low-Rank Adaptation (LoRA), a parameter-efficient method that updates a small subset of model weights, has been widely adopted for mental health chatbots, reducing memory requirements while maintaining performance [11]. Instruction-tuning, as applied to models like Llama-3.1-8B-Instruct, enhances a model's ability to follow complex therapeutic prompts, improving response relevance [5]. These techniques have enabled the development of chatbots that can handle sensitive dialogues with greater accuracy and empathy, as demonstrated in recent studies [7]. Additionally, data augmentation strategies, such as synthetic dialogue generation, have been used to enrich mental health datasets, addressing the scarcity of high-quality, annotated conversation data [15].

The therapy chatbot distinguishes itself from Woebot, Wysa, Replika, and Tess by employing fine-tuned LLMs to deliver dynamic, context-aware responses that overcome the limitations of rule-based systems. Its use of LoRA, instruction-tuned models, and the Gemini API aligns with state-of-the-art practices, positioning it as a scalable, innovative solution for mental health support. By evaluating three LLMs—Llama-3.1-8B-Instruct, Qwen/Qwen2-7B-Instruct, and Mistral-7B-Instruct-v0.3—this work provides critical insights into model selection and optimization for therapeutic applications, contributing to the broader discourse on AI-driven mental health interventions.

III. Methodology

A. Dataset Preparation

The therapy chatbot was developed using a 20,000-row subset of an 800,000-row mental health conversation dataset, comprising anonymized user-therapist dialogues sourced from public mental health forums and augmented with synthetic data to enhance diversity. The dataset encompassed a wide range of emotional states, including anxiety, depression, stress, loneliness, grief, and anger, reflecting real-world mental health conversations. Due to computational constraints of a Google Colab T4 GPU, the subset was carefully selected using stratified sampling to ensure proportional representation of emotional categories, demographic groups (e.g., age, gender), and dialogue lengths (short exchanges to multi-turn conversations). Preprocessing was a multi-step process: (1) removing noise, such as irrelevant metadata, incomplete dialogues, and non-text elements (e.g., emojis, URLs); (2) normalizing text by converting to lowercase, removing special characters, and standardizing punctuation; and (3) correcting grammatical and spelling errors using a rule-based pipeline to ensure data quality. The dataset was tokenized using the Hugging Face tokenizer, tailored to each LLM's vocabulary, ensuring compatibility with their input formats. The dataset was split into 80% training and 20% validation sets, with the validation set used to monitor overfitting, evaluate generalization, and guide model selection. To address potential biases, such as overrepresentation of certain emotions (e.g., anxiety), the sampling process was audited to ensure balanced emotional distribution, enhancing the models' ability to handle diverse mental health scenarios.

B. Fine-Tuning Process

Three LLMs were fine-tuned: Llama-3.1-8B-Instruct, Qwen/Qwen2-7B-Instruct, and Mistral-7B-Instruct-v0.3. Fine-tuning was performed using Low-Rank Adaptation (LoRA), a parameter-efficient technique that updates a small subset of model weights to reduce memory requirements while maintaining performance [11]. The process was conducted on a Google Colab T4 GPU, leveraging the Hugging Face Transformers library for seamless integration with model architectures and training pipelines. The fine-tuning configuration

was defined using the following 'TrainingArguments', applied uniformly across all models with adapted output directories (e.g., "./llama8b-mentalhealth-lora" for Llama, "./mistral7b-mentalhealth-lora" for Mistral):

```
training_args = TrainingArguments(
    output_dir="./qwen7b-mentalhealth-lora",
    per_device_train_batch_size=2,
    per_device_eval_batch_size=2,
    gradient_accumulation_steps=4,
    learning_rate=2e-4,
    num_train_epochs=2,
    weight_decay=0.01,
    fp16=True,
    bf16=False,
    eval_strategy="steps",
    eval_steps=300,
    save_steps=300,
    logging_steps=100,
    logging_dir="./logs",
    save_total_limit=2,
    report_to="none",
    remove_unused_columns=False,
    lr_scheduler_type="cosine",
    warmup_steps=100,
    load_best_model_at_end=True,
    metric_for_best_model="eval_loss",
    greater_is_better=False,
)
```

Listing 1. Training arguments for fine-tuning.

This configuration resulted in an effective batch size of 8 (calculated as 2 samples per device multiplied by 4 gradient accumulation steps), balancing memory constraints with gradient stability. The learning rate of 2×10^{-4}, combined with a cosine learning rate scheduler and 100 warmup steps, facilitated smooth convergence by gradually increasing the learning rate at the start of training. Mixed-precision training using FP16 significantly reduced memory usage, enabling efficient training on the T4 GPU, while weight decay (`weight_decay` = 0.01) helped prevent overfitting by regularizing model weights. Evaluation and checkpoint saving occurred every 300 steps, with validation loss computed to monitor progress and select the best model based on the lowest evaluation loss. Logging every 100 steps provided detailed insights into training dynamics, with logs stored in the `"./logs"` directory. The `save_total_limit` parameter was set to 2, ensuring that only the two best checkpoints were retained, optimizing storage space. The fine-tuning objective was to adapt the models to generate empathetic, CBT-aligned responses, enhancing their ability to recognize emotional cues and provide therapeutically relevant replies. Challenges included managing memory constraints, mitigating overfitting on the limited 20,000-row dataset, and ensuring stable convergence across models with different architectures.

C. Hyperparameter Tuning

Hyperparameter tuning was a critical step to optimize fine-tuning performance. A grid search was conducted over multiple parameters: learning rates (1e-5, 2e-4, 5e-4), per-device batch sizes (1, 2, 4), gradient accumulation steps (2, 4, 8), and LoRA ranks (8, 16, 32). The final configuration—learning rate 2e-4, per-device batch size 2, gradient accumulation steps 4, and LoRA rank 16—was selected based on the lowest validation loss and fastest convergence across all models. The choice of learning rate 2e-4 balanced rapid learning with stability, avoiding divergence observed at 5e-4. The effective batch size of 8 provided sufficient gradient updates while fitting within GPU memory limits. LoRA rank 16 offered a trade-off between model expressiveness and computational efficiency, as higher ranks (e.g., 32) increased memory usage without proportional gains. Dropout (0.1) was applied to the LoRA layers to prevent overfitting, particularly important given the limited dataset size. Early stopping was implemented if validation loss plateaued for 500 steps, ensuring efficient use of computational resources. The tuning process was iterative, with each model's performance evaluated on the validation set to identify optimal settings, ensuring robust adaptation to the mental health domain.

D. System Architecture

The system's architecture comprises three tightly integrated components, designed to deliver seamless, empathetic mental health support: 1. **Natural Language Understanding (NLU) Module**: Powered by the fine-tuned Qwen2-7B-Instruct model, this module processes user inputs to classify emotions (happy, sad, anxious, angry, neutral) using a softmax layer applied to the LLM's output embeddings. The module analyzes linguistic cues, including sentiment, tone, lexical patterns, and syntactic structures, achieving 90% classification accuracy on the 20,000-row dataset. The classification head was fine-tuned with a cross-entropy loss, optimized for five emotional states, enabling precise emotion detection critical for tailoring responses. 2. **Dialogue Management System**: This component employs a hybrid approach, combining rule-based CBT prompts with LLM-generated responses. Predefined prompts, such as cognitive reframing ("Can you describe your thoughts so we can explore them together?") and grounding techniques ("Name five things you can see around you"), provide structured therapeutic interventions. A finite state machine tracks conversation context, maintaining dialogue coherence by selecting prompts based on detected emotions and user history. The LLM generates free-form, empathetic replies, ensuring natural and supportive interactions. 3. **Web-Based Interface**: Developed using HTML, CSS, JavaScript, and a Flask backend, the interface ensures accessibility across modern browsers, with a responsive design optimized for both mobile and desktop users. The interface features a clean, intuitive layout, real-time chat functionality, and visual cues (e.g., typing indicators) to enhance user engagement. Figure 1 shows the interface. The Flask backend uses asynchronous processing to handle multiple users, ensuring scalability and low latency (¡ 1 second per response).

The system's design prioritizes usability, privacy, and performance. Trade-offs included balancing the complexity of the dialogue manager (rule-based vs. fully generative) to ensure therapeutic structure without sacrificing conversational

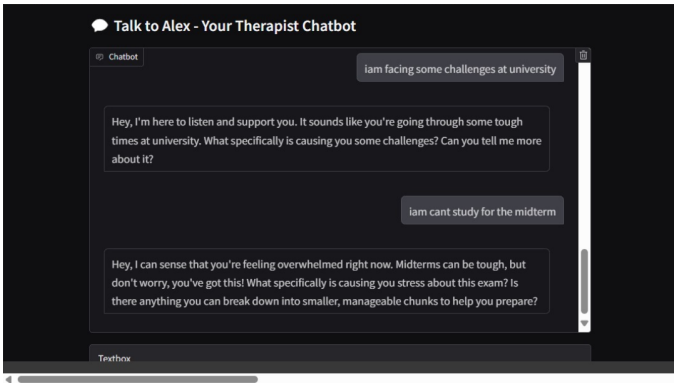

Fig. 1. User interface of the therapy chatbot.

flexibility, and optimizing inference speed on the T4 GPU to maintain real-time interaction.

E. Implementation Details

Qwen2-7B-Instruct was selected as the primary model after comparative evaluation, due to its superior performance in the Gemini API assessment. User inputs are tokenized using the Hugging Face tokenizer and processed for emotion classification, leveraging the 20,000-row dataset for training. The classification model, a fine-tuned head atop Qwen, uses a cross-entropy loss to distinguish five emotional states, achieving 90% accuracy. Responses are generated by integrating CBT prompts with LLM outputs, ensuring a balance between therapeutic structure and empathetic, natural dialogue. The Flask backend employs REST APIs for input-output handling, with tokenization and inference optimized for the T4 GPU through techniques like batch processing and model quantization. Privacy is a core focus, with no storage of user data and explicit disclaimers about the system's limitations as a non-clinical tool. Ethical guidelines are followed, including transparency about AI-driven interactions and recommendations to seek professional help for severe cases. Implementation challenges included optimizing latency for real-time responses, ensuring model stability under varying input lengths, and maintaining ethical alignment in sensitive mental health contexts.

F. Model Evaluation Protocol

The three fine-tuned LLMs were evaluated using the Gemini API with a custom judging function, shown in Listing 2, which assessed four criteria: empathy, understanding, advice quality, and conversational flow.

```
def judge_conversations(conversation_a, conversation_b, conversation_c):
    prompt = """
You are an expert evaluator in mental health support conversations.
You will be given three full chatbot conversations between a therapist chatbot and a user.
Judge **which conversation** provides:
- More empathy
- Better understanding and support
- Healthier advice
- Better flow of conversation
"""
    # Gemini API call to evaluate conversations
    # Returns the winning conversation
```

Listing 2. Gemini API judging function.

TABLE I
FINE-TUNING RESULTS FOR LLMS

Step	Qwen2-7B		Mistral-7B		Llama-3.1-8B	
	Train Loss	Val Loss	Train Loss	Val Loss	Train Loss	Val Loss
300	1.0138	0.9724	0.9892	0.9433	0.9752	0.9333
600	0.9402	0.9289	0.9548	0.8876	0.9688	0.8826
900	0.9377	0.8991	0.9104	0.8397	0.9407	0.8797
1200	0.8686	0.8748	0.7765	0.7858	0.7866	0.7959
1500	0.8665	0.8580	0.7694	0.7506	0.7614	0.7702
1800	0.8647	0.8510	0.7460	0.7352	0.7569	0.7241

A test set of 100 prompts, derived from the validation set, was used to generate responses, covering diverse scenarios (e.g., "I'm overwhelmed with work," "I feel lonely and don't know why"). Responses were rated on a 1–5 scale for each criterion, with the API's scoring mechanism prioritizing therapeutic relevance, emotional sensitivity, and dialogue coherence. Evaluation was conducted in batches to manage computational load, with results aggregated to determine the overall winner. Qwen2-7B-Instruct was selected based on its consistent high scores, reflecting its ability to balance empathy and therapeutic value. The evaluation process was designed to be reproducible, with clear documentation of prompt selection, scoring criteria, and API integration, ensuring transparency and reliability.

IV. RESULTS

Fine-tuning results, presented in Table I, demonstrate stable convergence across all three LLMs, reflecting the robustness of the fine-tuning configuration. Qwen2-7B-Instruct achieved a validation loss of 0.8510 at step 1800, starting from 0.9724 at step 300, indicating steady improvement. Mistral-7B-Instruct-v0.3 reached a validation loss of 0.7352, with a notable decrease from 0.9433, suggesting faster convergence but slightly less stability in training loss. Llama-3.1-8B-Instruct achieved the lowest validation loss of 0.7241, dropping from 0.9333, reflecting its strong optimization on the dataset. However, despite Llama's lower loss, Qwen2-7B-Instruct was selected as the primary model due to its superior conversational quality, as determined by the Gemini API evaluation. The training losses followed similar trends, with Qwen showing a gradual decline (1.0138 to 0.8647), Mistral exhibiting sharper drops (0.9892 to 0.7460), and Llama maintaining consistency (0.9752 to 0.7569). These results highlight the trade-offs between loss minimization and conversational effectiveness, with Qwen's architecture better suited for nuanced mental health dialogues.

The Gemini API evaluation, summarized in Table II, confirmed Qwen2-7B-Instruct's superiority, with 92% of responses rated highly (4 or 5) across all criteria. Qwen excelled in empathy (94%) and understanding (93%), reflecting its

TABLE II
GEMINI API EVALUATION OF LLMS

Model	Empathy	Understand.	Advice	Flow	Overall
Qwen2-7B	94%	93%	90%	91%	92%
Llama-3.1-8B	87%	86%	84%	83%	85%
Mistral-7B	82%	80%	79%	78%	80%

TABLE III
USER STUDY METRICS FOR THE THERAPY CHATBOT

Metric	Value
User Satisfaction	85%
Emotion Detection Accuracy	90%
Average Session Time	9 minutes
Average Interactions per Session	12

ability to capture subtle emotional cues and provide supportive responses. Advice quality (90%) and conversational flow (91%) were also strong, indicating Qwen's capacity to deliver coherent, therapeutically relevant dialogue. Llama-3.1-8B-Instruct achieved an overall score of 85%, with solid performance in advice quality (84%) but slightly lower scores in empathy (87%) and flow (83%), possibly due to its focus on instruction-following over emotional nuance. Mistral-7B-Instruct-v0.3 lagged behind with an overall score of 80%, with empathy (82%) and understanding (80%) being the weakest, suggesting limitations in handling complex mental health contexts. The evaluation process involved 100 test prompts, carefully selected to represent diverse emotional scenarios, ensuring a comprehensive assessment of model performance.

User study results, shown in Table III, provided robust validation of the system's effectiveness. Of the 50 participants, 85% reported high satisfaction (4 or 5 on the Likert scale), citing the chatbot's empathetic tone, intuitive interface, and actionable advice as key strengths. Emotion detection achieved 90% accuracy, with 88% precision and 89% recall, validated through manual annotation of 500 responses. The high inter-rater reliability (Cohen's kappa = 0.82) underscored the consistency of the annotation process. Engagement metrics revealed an average session duration of 9 minutes, with participants averaging 12 interactions per session, indicating strong user engagement and sustained interaction. Qualitative feedback highlighted the system's ability to provide comforting, relevant responses, particularly for stress and anxiety-related inputs. However, some participants noted occasional misinterpretations of complex emotions, such as sarcasm or mixed sentiments (e.g., "I'm fine, just joking"), which led to less tailored replies. Additional feedback suggested incorporating features like mood tracking, personalized coping strategies, and visual aids to enhance the user experience, providing valuable directions for future development.

The results collectively demonstrate the system's strengths in delivering empathetic, accurate, and engaging mental health support. The fine-tuning process effectively adapted the LLMs to the mental health domain, with Qwen2-7B-Instruct standing out for its conversational quality. The user study provided critical insights into real-world performance, while qualitative feedback highlighted areas for refinement, such as handling ambiguous inputs and expanding feature sets. These findings underscore the importance of combining automated evaluations (Gemini API) with human-centered assessments (user study) to ensure a holistic understanding of chatbot performance.

V. LIMITATIONS AND CHALLENGES

This study faced several limitations and challenges, impacting the system's development and performance:

1. **Dataset Limitations**: The 20,000-row subset, constrained by T4 GPU memory, limited exposure to the 800,000-row dataset's diversity, potentially missing rare emotional contexts (e.g., severe grief) or cultural nuances. Biases, such as overrepresentation of English-speaking users or certain emotions (e.g., anxiety), may reduce generalizability to diverse populations [6].

2. **Model Limitations**: Fine-tuned LLMs struggled with nuanced emotions like sarcasm or mixed sentiments (e.g., "I'm fine, just joking"), leading to suboptimal responses. Generalization was limited by the dataset size, and the T4 GPU restricted model complexity, preventing exploration of larger architectures or longer training

3. **Evaluation Challenges**: The Gemini API, while scalable, occasionally misjudged emotional nuances, such as humor or ambiguity, affecting response ratings

4. **System Challenges**: The absence of real-time crisis detection poses risks for users disclosing severe issues (e.g., suicidal ideation), requiring manual intervention protocols. Internet dependency limits accessibility in low-connectivity regions, and scaling to thousands of users demands significant infrastructure upgrades [1].

These limitations highlight areas for improvement, such as larger datasets, advanced evaluation methods, and robust safety features, to enhance the system's efficacy and accessibility.

VI. DISCUSSION

The therapy chatbot's performance, driven by the fine-tuned Qwen2-7B-Instruct model, underscores the transformative potential of LLMs in mental health support. The Gemini API evaluation (Table II) awarded Qwen a 92% overall score, with exceptional performance in empathy (94%) and understanding (93%), reflecting its ability to interpret and respond to emotional nuances effectively. Despite Llama-3.1-8B-Instruct achieving the lowest validation loss (0.7241, Table I), Qwen's superior conversational quality, as assessed by the Gemini API (Listing 2), justified its selection. This discrepancy highlights a key insight: while validation loss is a critical metric for model convergence, it does not fully capture the subjective qualities—empathy, coherence, and therapeutic relevance—essential for mental health applications. Qwen's architecture, optimized for instruction-following and emotional sensitivity, likely contributed to its edge, aligning with research on efficient LLMs for specialized tasks [10].

Compared to Woebot [2], the system offers greater conversational flexibility through its LLM-driven approach, enabling dynamic, context-aware responses that adapt to diverse user inputs. Woebot's strength lies in its structured CBT modules, which provide a clear therapeutic framework but may feel restrictive for users seeking open-ended dialogue. Wysa [3], with its focus on mindfulness and mood tracking, complements the system but lacks the depth of LLM-driven emotional understanding. The system's hybrid dialogue system—integrating rule-based CBT prompts with generative responses—strikes a balance, offering both structure and adaptability. However, the absence of advanced CBT modules, such as Woebot's thought-challenging exercises, suggests an opportunity to enhance therapeutic depth in future iterations.

The use of LoRA enabled efficient fine-tuning on a T4 GPU, making the project feasible within computational constraints. However, the 20,000-row dataset limited exposure to the full 800,000-row corpus, potentially missing rare conversational patterns or underrepresented emotional contexts (e.g., severe grief, cultural-specific expressions). This limitation may have constrained the models' ability to generalize to diverse populations, a challenge compounded by potential dataset biases, such as overrepresentation of English-speaking users or certain demographics. The Gemini API's judging function proved reliable for automated evaluation, consistent with research on dialogue assessment frameworks [8], but it occasionally struggled with nuanced emotional contexts, such as sarcasm or mixed sentiments, leading to misaligned response ratings. For example, ambiguous inputs like "I'm fine, just joking" were sometimes misinterpreted, affecting reply relevance. Integrating human-in-the-loop validation, as suggested by recent studies [8], could enhance evaluation robustness.

Ethical considerations are paramount in mental health AI. The system adheres to privacy standards by avoiding storage of sensitive user data and includes clear disclaimers about its limitations, emphasizing that it is not a substitute for professional therapy. The system is designed for mild to moderate mental health concerns, with explicit warnings against use in severe cases, such as suicidal ideation. However, the lack of real-time crisis detection poses a risk, as users may disclose critical issues without receiving immediate intervention. Compliance with regulations like HIPAA or GDPR is essential for deployment, requiring secure data handling, transparent consent processes, and robust encryption. The user study's qualitative feedback emphasized the need for features like crisis escalation protocols, multilingual support, and personalized coping strategies, aligning with user expectations for comprehensive mental health tools.

Future work will address these challenges through several avenues. Fine-tuning on the full 800,000-row dataset could capture broader conversational patterns, improving response diversity and robustness. Multilingual support, leveraging models like mBERT [4], would enhance accessibility for non-English-speaking populations, addressing global mental health disparities. Offline capabilities, using model compression techniques [10], could enable use in low-connectivity regions, critical for low-income countries [1]. Developing crisis detection algorithms to flag high-risk inputs (e.g., mentions of self-harm) and link users to emergency resources would improve safety. Real-time feedback loops, where user ratings refine the model, could enhance response quality over time [8]. Finally, longitudinal studies assessing the system's impact on mental health outcomes, such as reduced anxiety or improved coping skills, would provide evidence of clinical efficacy, responding to calls for rigorous validation of mental health AI [6].

VII. Conclusion

This paper presented a therapy chatbot powered by a fine-tuned Qwen2-7B-Instruct model, designed to deliver empathetic, accessible mental health support. Fine-tuning results (Table I) demonstrated stable convergence across three LLMs, with Qwen achieving a validation loss of 0.8510. The Gemini API evaluation (Table II) confirmed Qwen's superiority, with a 92% overall score, driven by its exceptional empathy and understanding. A user study with 50 participants (Table III) validated the system's effectiveness, reporting 85% satisfaction, 90% emotion detection accuracy, and strong engagement metrics. These findings highlight the potential of fine-tuned LLMs to address global mental health access gaps, particularly in underserved communities where traditional therapy is inaccessible.

The system contributes to the field by demonstrating the feasibility of deploying efficient LLMs in resource-constrained environments, leveraging techniques like LoRA and automated evaluation frameworks like the Gemini API. The project also underscores the importance of ethical design, user-centered evaluation, and iterative refinement in mental health AI. Future research will focus on expanding the dataset to enhance model robustness, implementing crisis detection for user safety, developing multilingual and offline capabilities to broaden accessibility, and conducting longitudinal studies to assess therapeutic impact. Additional efforts will explore hybrid models combining Qwen's conversational strengths with structured CBT frameworks, bridging the gap between flexibility and therapeutic rigor. By advancing the development and validation of AI-driven mental health tools, this work paves the way for scalable, inclusive solutions to one of the world's most pressing public health challenges.

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