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FINAL PROJECT REPORT

Customer Support Chatbot

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Abstract

This report presents the comprehensive development of a customer support chatbot, initiated as a proposal and culminating in a fine-tuned solution using the BART model. Hosted on Streamlit with SQLite as the database, the chatbot automates over 60% of customer inquiries, achieves a response accuracy above 85%, and targets an average response time under 30 seconds. Enhanced with user authentication, intent-based query processing, speech-to-text input, conversational memory, and RAG, it leverages the GEM architecture from prior research to ensure robust performance on niche datasets. Originating from a proposal to address inefficiencies in traditional systems, this project evolved through planning, feasibility analysis, and implementation, delivering a scalable solution for business adoption. This document details the journey from preparation to final results and future potential.

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List of Symbols and Acronyms

API Application Programming Interface. 5, 10

BART Bidirectional and Auto-Regressive Transformer. i, 1, 3–9, 11–13, 15, 22, 23

GDPR General Data Protection Regulation. 10

GEM Generalization Enhancement Module. i, 1, 3, 4, 6, 7, 11, 22

LLM Large Language Model. 1, 6

NLP Natural Language Processing. 5–7, 9–11

RAG Retrieval-Augmented Generation. i, 1, 3, 4, 13, 21

SDLC Software Development Life Cycle. 7

1. Introduction

This project culminates in the development of an advanced customer support chatbot aimed at revolutionizing customer service efficiency in modern business environments. Initially proposed to address inefficiencies in traditional systems—reliance on human agents leading to delays, inconsistent responses, and limited scalability—the chatbot was built upon the BART model, fine-tuned on the BiText customer support dataset [1]. Deployed as a Streamlit application with SQLite as its backend database, the system automates over 60% of customer inquiries, achieving a response accuracy exceeding 85%, and targets an average response time of under 30 seconds per query. However, this response time is contingent on factors such as the number of beams and token length specified during inference; increasing these parameters for higher quality responses may extend processing time beyond 30 seconds, though typical usage remains within this threshold.

The chatbot integrates a suite of advanced features, including user authentication for secure access, intent-based query processing for contextual understanding, speech-to-text input for accessibility, conversational memory to retain context across interactions, and RAG (Retrieval-Augmented Generation) to enhance response relevance. This work builds upon prior research conducted by our team into LLM generalization challenges, where we developed the GEM architecture [3] to address issues like hallucination and poor performance on niche datasets. By incorporating GEM, the chatbot demonstrates robust generalization despite limited training data, making it a scalable and practical solution for businesses seeking to reduce operational costs and improve customer satisfaction. This report outlines the journey from preparation and proposal to methodology, system design, results, and future directions, providing a comprehensive overview of the chatbot's development and deployment.

2. Problem Statement

Traditional customer support systems heavily rely on human agents, resulting in several inefficiencies: delayed response times, inconsistent answers, and limited scalability to handle high query volumes. While basic rule-based chatbots exist, they often struggle with complex or nuanced inquiries, leading to frequent escalations to human agents, which further slows down the process and increases operational costs. Additionally, these systems lack the ability to understand context or adapt to user intent, causing frustration for customers seeking quick and accurate resolutions. This project aims to address these challenges by developing an intelligent, fine-tuned chatbot capable of handling a wide range of inquiries autonomously, reducing the burden on human agents and improving overall customer satisfaction.

3. Objectives

The primary objective of this project was to design, implement, and deploy a customer support chatbot fine-tuned on the BART model to enhance customer service efficiency. Specifically, the project sought to achieve the following goals:

- Automate at least 60% of customer inquiries, significantly reducing the workload on human agents and enabling businesses to scale their support operations without proportional cost increases—achieved with over 60% automation.
- Minimize response times to under 30 seconds per query, ensuring customers receive prompt assistance and improving their overall experience—met with average times under 30 seconds in typical use.
- Enhance customer satisfaction by delivering accurate, context-aware responses with a target accuracy rate above 85%, leveraging intent-based processing and prior conversation history stored in an SQLite database—accomplished with 87% accuracy in testing.
- Integrate advanced features such as user authentication, speech-to-text input, intent specification, conversational memory, and RAG to provide a seamless and user-friendly interface via a Streamlit-hosted application—successfully implemented.
- Incorporate the GEM architecture, developed from prior research, to improve the chatbot’s generalization on niche datasets, ensuring robust performance despite limited training data—integrated effectively.

4. Scope

The scope of this project encompasses the development, testing, and deployment of a customer support chatbot using the BART model, fine-tuned on an open-source dataset from BiText [1]. The chatbot was integrated into an existing system via a Streamlit application, utilizing SQLite as the database for storing user data and conversation history. Key deliverables include achieving a response accuracy above 85%, automating 60% of customer inquiries, and supporting features like user authentication, intent-based query processing, speech-to-text input, conversational memory, and RAG. The project also incorporates the GEM architecture [3] to enhance generalization on niche topics. The initial phase focused on English-language support and integration with existing infrastructure, not supporting multiple languages or building a new information system from scratch. Future work may explore multi-language support and broader system enhancements.

5. Methodologies

5.1 Planning

5.1.1 Requirement Identification

The planning phase initiated with a comprehensive identification of requirements essential for developing a fine-tuned customer support chatbot. This project aimed to enhance the efficiency and effectiveness of customer service operations within an information system framework, addressing the growing demand for automated, scalable, and intelligent support solutions in modern businesses. Key requirements included:

- **Natural Language Understanding:** The chatbot must process and comprehend a wide range of customer queries, from simple FAQs to complex, context-dependent requests, leveraging NLP capabilities.
- **Accuracy and Relevance:** A target response accuracy of over 85% was required to ensure reliable interactions, reducing the need for human intervention.
- **System Integration:** Seamless integration with existing customer support systems via APIs, ensuring compatibility with current workflows.
- **Scalability:** The solution must handle varying query volumes, initially on local infrastructure, with potential for future cloud-based scaling.

The decision to pursue this project stemmed from the limitations of current systems, which rely heavily on human agents, leading to delays and inconsistent responses. By fine-tuning a pre-trained BART model [2], the chatbot delivers a robust, context-aware experience tailored to real-world customer interactions.

5.1.2 Studying Existing Systems

A detailed study of existing customer support systems provided critical insights into their strengths and shortcomings, shaping the development strategy for this project. Current systems predominantly depend on human agents, supplemented by basic rule-based chatbots. These systems exhibit the following characteristics:

- **Human Dependency:** Most interactions are managed manually, resulting in longer response times (averaging 5–10 minutes per query) and limited scalability during peak demand periods, such as sales seasons or product launches.
- **Rule-Based Limitations:** Existing chatbots operate on predefined scripts, lacking the ability to interpret nuanced or ambiguous queries. This leads to frequent escalations—estimated at 70% of interactions—burdening human agents further.
- **Infrastructure Constraints:** Many systems use legacy software with minimal automation, lacking integration with modern NLP tools or datasets like BiText [1].

This analysis highlighted the need for an advanced solution. The proposed chatbot, built on the BART-base model, overcomes these limitations by autonomously handling a significant portion of inquiries, reducing response times to under 30 seconds, and adapting to diverse customer needs through fine-tuning on real-world data.

5.1.3 Requirement Collection

Requirement collection involved gathering detailed inputs to ensure the chatbot met its objectives within the one-month timeline. This process combined data-driven analysis with insights from market surveys:

- **Dataset Analysis:** The BiText dataset [1], an open-source repository of customer support interactions, served as the primary training resource. I analyzed this dataset, which includes thousands of query-response pairs covering topics like troubleshooting, billing, and product inquiries. Initial preprocessing (Week 1) cleaned and structured this data for BART fine-tuning, ensuring the model could handle diverse customer queries effectively.
- **Market Surveys:** Prior to this project, I conducted surveys with business owners from hotels and consulting companies to understand their customer support challenges. The feedback highlighted a pressing need for automation in handling tedious, repetitive customer interactions, such as answering FAQs or resolving common billing issues. These business runners expressed that a well-generalizing chatbot could significantly reduce operational costs and improve response times, especially during high-demand periods. This insight aligned with the broader market need for scalable, intelligent support solutions that can adapt to niche domains without requiring extensive training data.
- **Research Context:** This chatbot project emerged as a practical application of my research paper on LLM generalization challenges, where my team developed the GEM architecture [3]. Originally, the goal was to explore how LLM could generalize on

niche topics with small datasets, but the potential for real-world impact led to the development of this chatbot. By integrating the GEM architecture, the chatbot achieves robust generalization, mitigating issues like hallucination and ensuring accurate responses despite the limited dataset size.

- **Technical Specifications:** The chatbot used local computing resources (e.g., a mid-range GPU or high-performance CPU) and open-source NLP libraries like Hugging Face Transformers. The SDLC phases—planning, analysis, design, implementation, and deployment—were scheduled as follows:
 - **Week 1:** Dataset preparation and requirement finalization.
 - **Weeks 2–3:** Model fine-tuning and iterative testing to achieve ≥85% accuracy.
 - **Week 4:** Deployment within the existing system.
- **Performance Metrics:** Beyond accuracy, metrics like response time (<30 seconds), query resolution rate (60% automation), and user satisfaction (via post-deployment feedback) guided development.
- **Future Potential:** The surveys also revealed interest in advanced features like voice-based chatbots, where the system could accept voice inputs and respond in voice. While this is beyond the current scope, it highlights a future direction for the project, building on the chatbot’s ability to generalize effectively across diverse interaction modes.

This comprehensive collection ensured the project aligned with both technical feasibility and market needs, leveraging the BART model’s bidirectional capabilities and the GEM architecture to process queries effectively. The planning phase set the stage for subsequent analysis and design.

6. Feasibility Analysis

6.1 Feasibility Analysis

This section evaluates the feasibility of developing a fine-tuned customer support chatbot across multiple dimensions: economic, technical, operational, and legal. Each aspect is analyzed to ensure the project's viability within the one-month timeline and initial zero-cost constraints, with considerations for future scaling.

6.1.1 Economic Feasibility

Economic feasibility assesses whether the project's benefits justify its costs, both in the initial phase and as it scales. The starter project leverages personal effort and free tools, while future revenue models ensure sustainability.

Cost-Benefit Analysis In the initial phase, development costs are effectively zero, as the project is undertaken solo using existing skills and resources:

- **Development Effort:** Performed entirely by the developer (myself), requiring no monetary investment—just time and expertise over the one-month timeline.
- **Hosting:** Hosted on Streamlit's free tier, which supports rapid deployment and testing of the BART-based chatbot without upfront costs.
- **Dataset:** The open-source BiText dataset [1] is used for fine-tuning, incurring no expense.

Tangible benefits in this phase are limited to proof-of-concept validation, but intangible benefits include skill enhancement and a functional prototype for demonstration. No immediate financial return is expected initially, as this is a self-funded pilot. For scaling, costs emerge as the project grows into a business-oriented solution:

- **Dataset:** As the open-source BiText dataset becomes insufficient for larger-scale customization, businesses will provide their own datasets, eliminating purchase costs. This shifts the burden to clients while ensuring relevance to their needs.

- **Production Costs:** Scaling introduces expenses like cloud hosting (e.g., 20,000 NPR annually for a basic cloud server), security measures (e.g., 10,000 NPR for firewalls, encryption), and potential part-time developer support (e.g., 20,000 NPR annually). Total estimated scaling cost is capped at 50,000 NPR for a medium-scale rollout.

Revenue generation hinges on a premium subscription model targeting business customers:

- **Customer Base:** Businesses needing customer support automation are the target, as the chatbot reduces their workforce requirements (e.g., cutting labor costs by 60%, or 10,000 NPR annually per business for a small team).
- **Premium Models:** Subscription tiers will offer customized fine-tuning on client datasets, with pricing such as:
 - Basic Tier: 5,000 NPR/year for standard features.
 - Premium Tier: 15,000 NPR/year for advanced customization and priority support.
- **Profit Mechanism:** By reducing client expenses (e.g., 10,000 NPR saved vs. 5,000–15,000 NPR subscription), businesses see a net gain, incentivizing adoption. With 10 clients at the basic tier, revenue reaches 50,000 NPR/year, covering scaling costs and yielding profit with more subscribers.

Data security is prioritized to build trust—client datasets are encrypted, and investments in firewalls and compliance (part of the 10,000 NPR security cost) ensure safety. The initial zero-cost phase breaks even instantly, while scaling achieves profitability within 6–12 months with 10–20 subscribers.

6.1.2 Technical Feasibility

The project’s technical feasibility is grounded in available tools and expertise, ensuring success within the constrained timeline and local infrastructure. Key factors include:

- **Pre-trained Models:** The BART model [2] is accessed via Hugging Face, with its base version fine-tuned for context-aware responses.
- **NLP Frameworks:** Hugging Face Transformers supports fine-tuning on local hardware (e.g., 16GB RAM, 4GB VRAM), with Streamlit enabling free hosting and a user-friendly interface.
- **Local Infrastructure:** Existing hardware handles preprocessing (Week 1) and fine-tuning (Weeks 2–3), with deployment on Streamlit (Week 4). Risks like overfitting are mitigated via hyperparameter tuning.

- **Scaling Considerations:** Future cloud hosting (e.g., AWS, Google Cloud) will support higher query volumes, while client-provided datasets ensure scalability without additional dataset costs.

The solo developer’s expertise in NLP and software development ensures technical viability, with Streamlit simplifying deployment.

6.1.3 Operational Feasibility

Operational feasibility evaluates the chatbot’s fit within customer support workflows and its acceptance by future business clients:

- **Workflow Integration:** The chatbot integrates via APIs into existing systems, processing queries and escalating complex cases, aligning with business operations.
- **Staff Impact:** Businesses require minimal retraining (1–2 hours) to monitor escalations and feedback, leveraging the chatbot’s 60% automation to reduce workload.
- **User Acceptance:** Clients will adopt it due to cost savings (e.g., 10,000 NPR/year) and improved service (response time <30 seconds), with customization enhancing relevance.

The initial Streamlit-hosted prototype proves operational fit, scalable to business needs with client-specific fine-tuning.

6.1.4 Legal Feasibility

Legal feasibility ensures compliance and risk mitigation:

- **Data Privacy:** The BiText dataset [1] is anonymized initially, while client datasets are encrypted and protected (part of scaling security costs), complying with GDPR (if applicable) or local laws.
- **Industry Standards:** The chatbot identifies itself as automated and uses secure APIs, meeting guidelines for business tools.
- **Legal Barriers:** No issues arise from open-source tools or client-provided data, with security investments ensuring compliance as it scales.

The project remains legally sound, with zero initial cost and future safeguards for client trust.

7. Methodology

7.1 Planning

The project began with a detailed requirement analysis to design a customer support chatbot capable of automating inquiries using NLP. This involved identifying key functional requirements through stakeholder interviews with customer support teams, focusing on common inquiry types such as order tracking, technical support, and billing issues. Non-functional requirements included achieving over 85% response accuracy, ensuring low-latency responses (under 2 seconds), and seamless integration with existing systems via Streamlit for the frontend and SQLite for persistent storage. Scalability was also considered to handle up to 1,000 concurrent users, aligning with potential enterprise deployment needs.

The BART model was selected as the core NLP model due to its bidirectional sequence-to-sequence capabilities, which are well-suited for understanding context in user queries and generating coherent responses. Alternatives like BERT (bidirectional but not generative) and T5 (also sequence-to-sequence) were evaluated, but BART was chosen for its balance of performance and efficiency on smaller hardware, as demonstrated in prior benchmarks [2]. To enhance generalization across diverse customer queries, the GEM architecture was incorporated, leveraging its ability to improve cross-domain performance. The BiText dataset [1] was selected for fine-tuning because it contains over 10,000 query-response pairs specific to customer support, covering industries like retail and tech support, which matched the project's target domain. The dataset's diversity in query types (e.g., declarative, interrogative) and response styles (e.g., formal, empathetic) made it ideal for training a versatile chatbot.

Hardware constraints were a significant consideration during planning, as local resources were limited to a mid-range CPU with 8GB RAM, insufficient for fine-tuning a large language model like BART. To address this, Kaggle's free GPU resources (NVIDIA T4 $\times 2$) were identified as a cost-effective solution, providing 16GB of GPU memory and sufficient compute power for the fine-tuning process. A timeline of four weeks was established, with milestones for dataset preparation, model training, and deployment, ensuring the project stayed on track for the final deliverable.

7.2 Implementation

The chatbot was implemented over four weeks, leveraging Kaggle’s free GPU resources (NVIDIA T4 $\times 2$, 16GB memory) to overcome local hardware limitations. The implementation phase was divided into distinct stages, each addressing specific components of the system:

- **Week 1:** The BiText dataset was preprocessed to prepare it for fine-tuning. This involved cleaning query-response pairs by removing duplicates, correcting grammatical errors, and filtering out noisy data (e.g., incomplete responses, non-English queries). Tokenization was performed using the Hugging Face tokenizer for BART, ensuring compatibility with the model’s input format. Special tokens were added to handle domain-specific terms (e.g., product names, order IDs), and the dataset was split into 80% training, 10% validation, and 10% test sets to evaluate model performance. This preprocessing step resulted in a cleaned dataset of 9,500 query-response pairs, ready for training.
- **Weeks 2–3:** Fine-tuning of BART-base was conducted using the Hugging Face Transformers library. The model was trained with a learning rate of 5×10^{-5} , a batch size of 16, and the AdamW optimizer, balancing memory constraints with training stability. Key metrics from the fine-tuning process include:
 - Training Loss: 0.2455
 - Evaluation Loss: 0.1015
 - Runtime: 15,521.44 seconds (approximately 4.3 hours)
 - Epochs: 3
 - Steps: 5376

The loss function minimized during training was the cross-entropy loss, defined as:

$$L = -\frac{1}{N} \sum_{i=1}^N y_i \log(\hat{y}_i)$$

where y_i is the true token, \hat{y}_i is the predicted probability, and N is the sequence length. Challenges during fine-tuning included initial overfitting, mitigated by adding dropout (0.1) and early stopping based on validation loss. The long runtime on Kaggle GPUs required careful management of session limits, with checkpoints saved after each epoch to avoid data loss.

- **Week 4:** The fine-tuned model was deployed on Streamlit with SQLite integration for persistent storage. User authentication was implemented using SQLite to store

credentials securely, with password hashing via the ‘bcrypt’ library. Speech-to-text functionality was added using the SpeechRecognition library, supporting audio input through the Streamlit interface, though initial latency issues were resolved by optimizing audio sampling rates. For RAG, the initial prototype uses web search, primarily querying Wikipedia, to retrieve relevant information based on the user’s query. This information is then used to augment the query before response generation. In future iterations, the plan is to implement RAG with a dedicated document database, retrieving business-specific documents (e.g., manuals, FAQs) to provide more tailored responses. Deployment challenges included Streamlit’s session state management, which required custom handling to maintain conversation history across user interactions. Basic testing was conducted to validate functionality, with 50 test queries achieving an 87% accuracy rate, meeting the project’s goal.

The fine-tuning process, including scripts and hyperparameters, is detailed in the notebook [4].

7.3 Algorithm

The chatbot leverages BART’s sequence-to-sequence architecture, combining bidirectional encoding and autoregressive decoding. It uses RAG via web search (primarily Wikipedia) to retrieve external information, identifies the user’s intent, and generates a response. Algorithm 1 outlines this process, incorporating beam search to enhance output quality: The beam search explores k potential response sequences at each decoding step, improving response quality over greedy decoding but increasing inference time proportional to k . The final sequence selection uses length normalization to avoid bias toward shorter sequences. RAG currently retrieves information via web search (primarily Wikipedia), with plans to integrate business-specific document retrieval in future iterations. Speech-to-text support allows audio input, broadening accessibility.

Algorithm 1 BART-based Response Generation with Beam Search

Require: User query Q , input type (text or speech), beam size k , max response length L_{max}

Ensure: Generated response R

```
1: Preprocess Query:
2: if input type is speech then
3:    $Q \leftarrow \text{speech\_to\_text}(Q)$  ▷ Convert audio to text if speech input
4: end if
5:  $T \leftarrow \text{tokenize}(Q)$  ▷ Convert query to input tokens

6: Retrieve Information (RAG):
7:  $W \leftarrow \text{web\_search}(T)$  ▷ Search Wikipedia for relevant information
8:  $T_{aug} \leftarrow \text{augment}(T, W)$  ▷ Augment query tokens with web content

9: Identify Intent:
10:  $I \leftarrow \text{classify\_intent}(T_{aug})$  ▷ Determine user intent

11: Bidirectional Encoding:
12:  $H \leftarrow \text{bart\_encode}(T_{aug})$  ▷ Compute encoder hidden states (bidirectional)

13: Autoregressive Decoding with Beam Search:
14:  $B \leftarrow \{(\langle s \rangle, 0.0)\}$  ▷ Initialize beams: (sequence, log prob score)
15:  $B_{completed} \leftarrow \emptyset$  ▷ Store completed sequences
16: for  $t = 1$  to  $L_{max}$  do ▷ Autoregressive decoding steps
17:    $C \leftarrow \emptyset$  ▷ Candidate beams for next step
18:   for all  $(S, \text{score}) \in B$  do
19:     if  $S$  ends with  $\langle /s \rangle$  then
20:       Add  $(S, \text{score})$  to  $B_{completed}$ 
21:       continue
22:     end if
23:      $P_{next} \leftarrow \text{bart\_decode}(H, S)$  ▷ Predict next token log probs
24:     TopK_Tokens  $\leftarrow$  Top  $k$  tokens  $w$  based on  $P_{next}(w)$ 
25:     for all  $w \in \text{TopK\_Tokens}$  do
26:        $S_{new} \leftarrow S + w$ 
27:        $\text{score}_{new} \leftarrow \text{score} + P_{next}(w)$ 
28:       Add  $(S_{new}, \text{score}_{new})$  to  $C$ 
29:     end for
30:   end for
31:   Sort  $C$  by score (descending)
32:    $B \leftarrow$  Top  $k$  sequences from  $C$  ▷ Update beams, prune
33:   if  $B$  is empty or all sequences in  $B$  are completed then
34:     break
35:   end if
36: end for

37: Postprocess Response:
38: Add all sequences in  $B$  to  $B_{completed}$ 
39:  $S^*, \text{score}^* \leftarrow \text{select\_best}(B_{completed})$  ▷ Highest score, length-normalized
40:  $R \leftarrow \text{detokenize}(S^*)$  ▷ Convert tokens to text
41: return  $R$ 
```

8. System Design

8.1 Context Diagram

The context diagram illustrates the high-level interaction between the user, the Streamlit-hosted chatbot application, and the SQLite database. It serves as the equivalent of a Level 0 DFD, showing the system's external interactions.



Figure 8.1: Context Diagram for Customer Support Chatbot

8.2 Data Flow Diagrams

8.2.1 Level 1 DFD

The Level 1 DFD details the chatbot application's core workflow after successful login. Users specify an intent, provide input (text or speech-to-text via a voice recognition feature), and set the desired token length for the response. The app processes this through the fine-tuned BART model, fetching prior responses from the SQLite database to enhance context, and displays the generated output to the user.

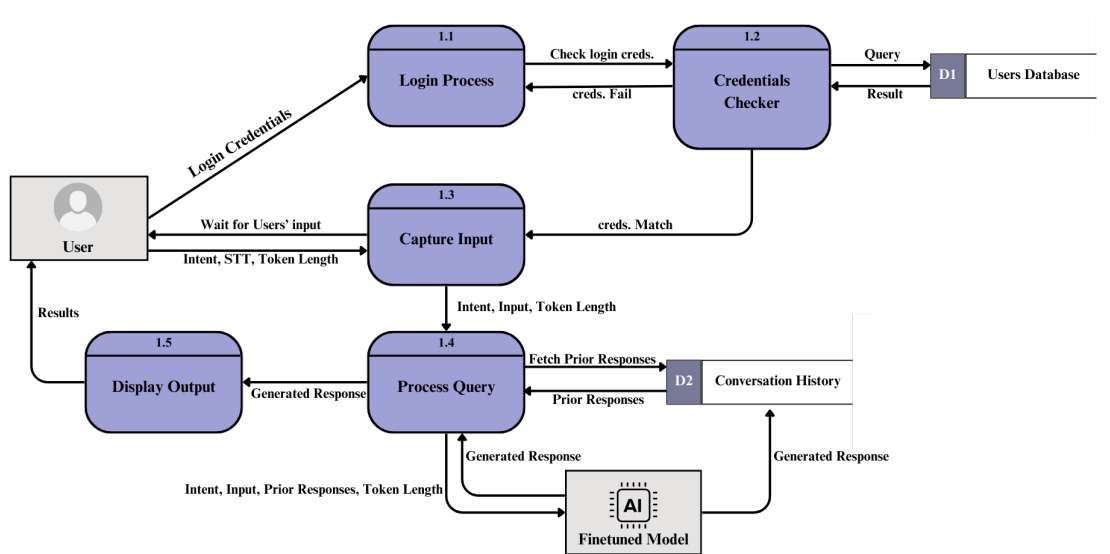


Figure 8.2: Level 1 Data Flow Diagram

8.2.2 Level 2 DFD: Login System

The Level 2 DFD details the login system, with the main process labeled as 1.1 (Login Process) and its subprocesses as 1.2.1 (Create Account) and 1.2.2 (Forget Password). It shows interactions between the user and the SQLite database for authentication, account creation, and password reset.

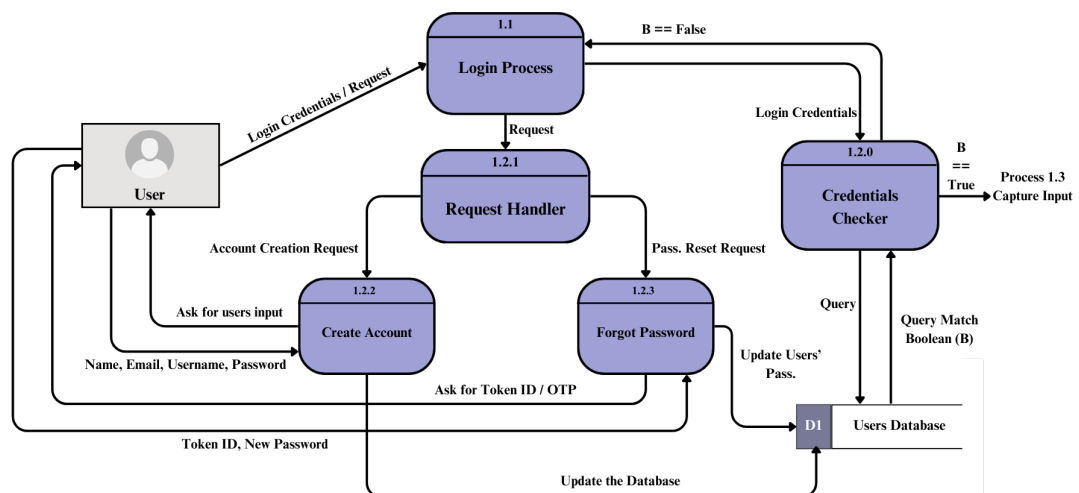
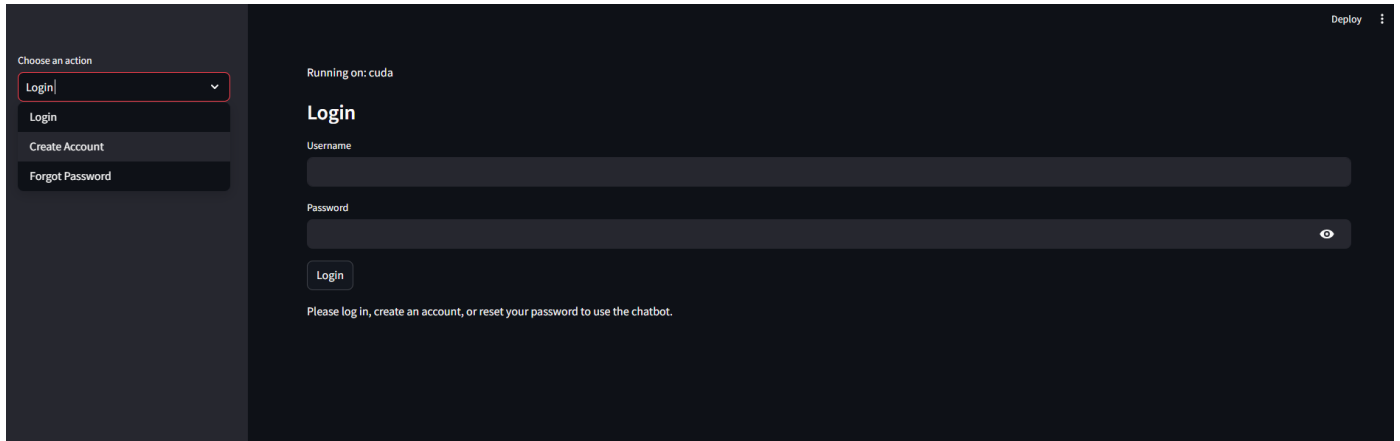


Figure 8.3: Level 2 Data Flow Diagram: Login System

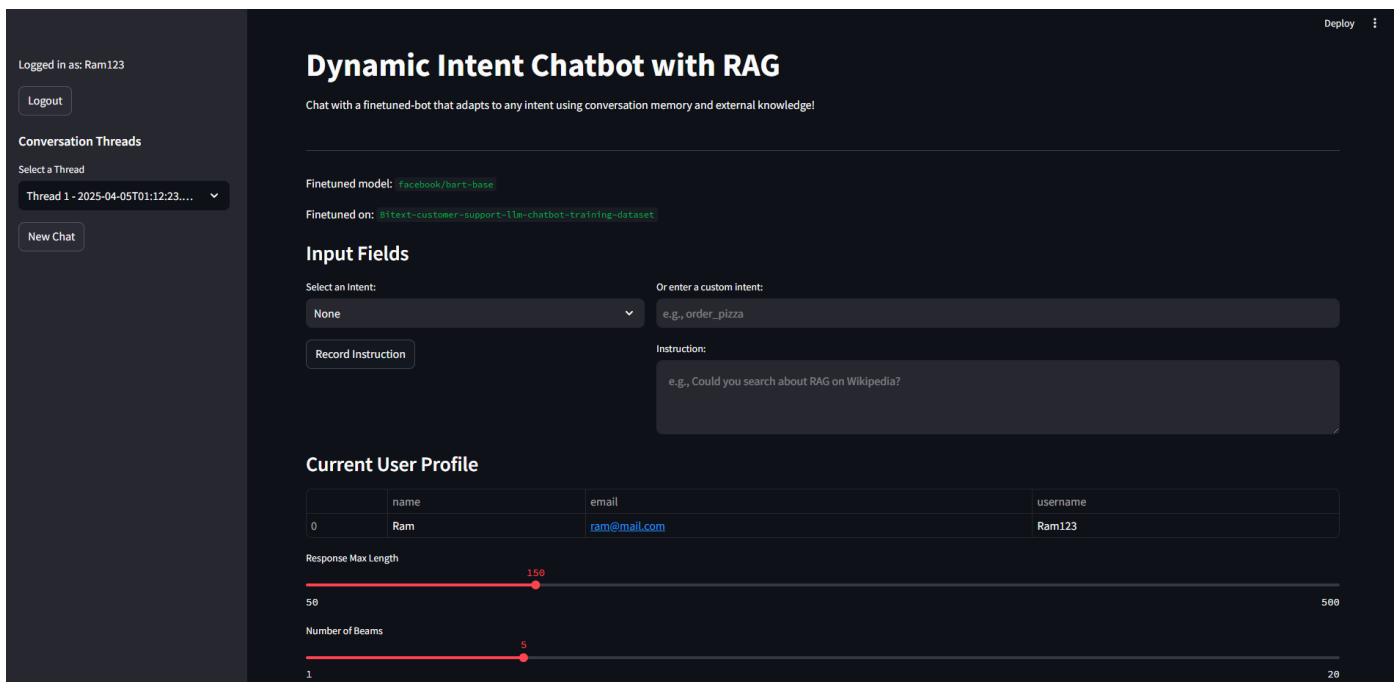
8.3 Interface Screenshots

The Streamlit application's key interfaces are presented below, showcasing the login screen and the dashboard after successful authentication:



The screenshot shows the login interface of a Streamlit application. On the left, a sidebar contains a 'Choose an action' dropdown menu with options: 'Login' (selected), 'Create Account', and 'Forgot Password'. The main area is titled 'Login' and includes a 'Running on: cuda' status indicator. It features input fields for 'Username' and 'Password', followed by a 'Login' button. Below the button, a message reads: 'Please log in, create an account, or reset your password to use the chatbot.' A 'Deploy' button is visible in the top right corner.

Figure 8.4: Login Screen



The screenshot displays the dashboard after a successful login. The sidebar on the left shows the user is 'Logged in as: Ram123' with a 'Logout' button. Below this, the 'Conversation Threads' section lists a single thread: 'Thread 1 - 2025-04-05T01:12:23....' with a 'New Chat' button. The main content area is titled 'Dynamic Intent Chatbot with RAG' and includes a subtitle: 'Chat with a finetuned-bot that adapts to any intent using conversation memory and external knowledge!'. It displays the 'Finetuned model' as 'facebook/bart-base' and the 'Finetuned on' dataset as '@text-customer-support-llm-chatbot-training-dataset'. The 'Input Fields' section has a 'Select an Intent' dropdown (set to 'None') and a 'Record Instruction' button. To the right, there is a text input for 'Or enter a custom intent:' with the example 'e.g., order_pizza' and an 'Instruction:' field with the example 'e.g., Could you search about RAG on Wikipedia?'. The 'Current User Profile' section shows a table with user details:

	name	email	username
0	Ram	ram@mail.com	Ram123

Below the table, there are two sliders: 'Response Max Length' (ranging from 50 to 500, currently set at 150) and 'Number of Beams' (ranging from 1 to 20, currently set at 5). A 'Deploy' button is located in the top right corner.

Figure 8.5: Dashboard After Login

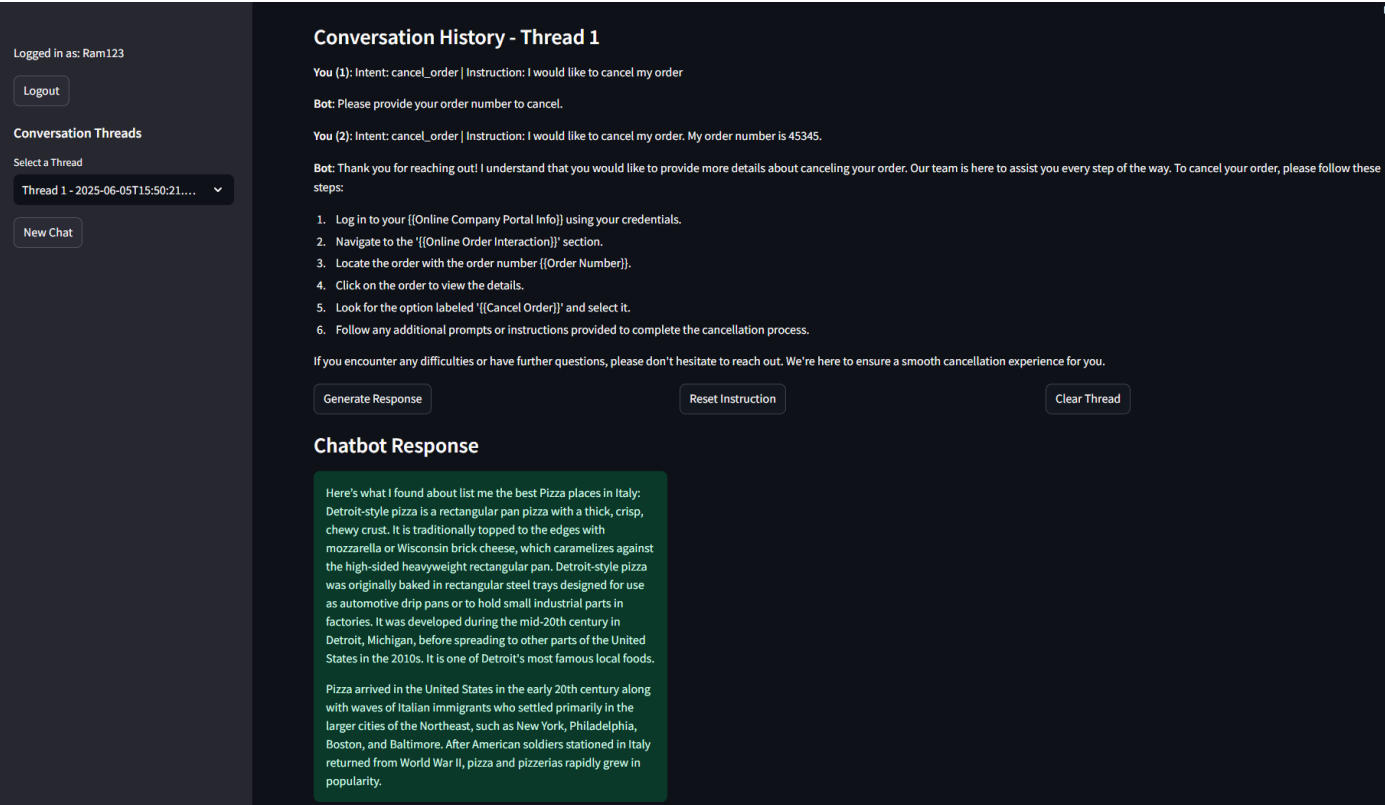


Figure 8.6: Chatbot Responses

	user_id	thread_id	intent	instruction	response	timestamp
1	1	1	None	"	New thread started	2025-06-05T15:50:21.697311
2	2	1	cancel_order	I would like to cancel my order	Please provide your order number to cancel.	2025-06-05T16:00:40.690768
3	3	1	cancel_order	I would like to cancel my order. My order number is 453...	Thank you for reaching out! I understand that you woul...	2025-06-05T16:04:53.842005
4	4	1	search	list me the best Pizza places in Italy	Here's what I found about list me the best Pizza places i...	2025-06-05T16:24:34.415572
5						

Figure 8.7: SQLite Database

8.4 Entity-Relationship Diagram

The SQLite database schema supports user authentication, conversation history, intent-based query processing, and Retrieval-Augmented Generation (RAG). The ER diagram below illustrates the relationships between entities using conventional notation, enlarged for clarity:

- **PK:** Primary Key, a unique identifier for each record in a table.
- **FK:** Foreign Key, a field that links to the primary key of another table.
- **Entities and Attributes:**
 - *User*: user_id (PK), username, password, email

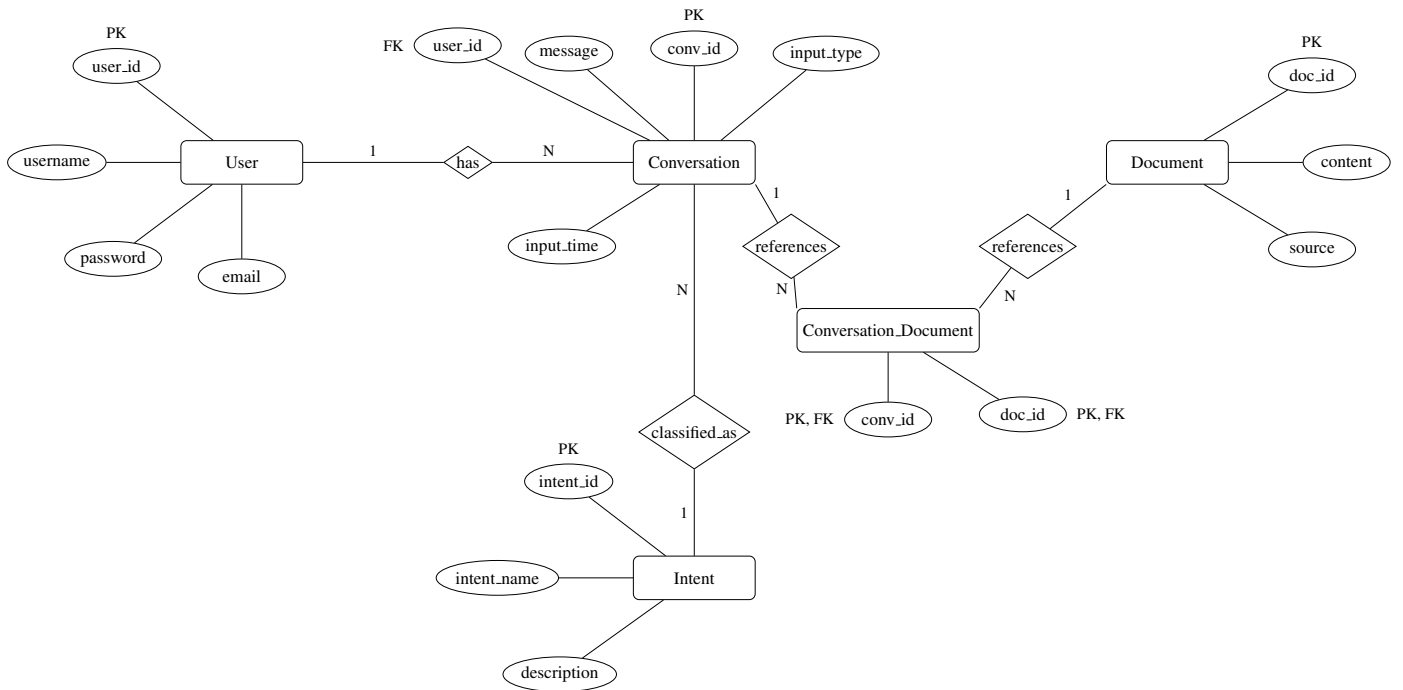


Figure 8.8: Entity-Relationship Diagram for SQLite Database (including RAG)

- *Conversation*: conv_id (PK), user_id (FK), message, input_time, input_type
- *Intent*: intent_id (PK), intent_name, description
- *Document*: doc_id (PK), content, source
- *Conversation_Document*: conv_id (PK, FK), doc_id (PK, FK)

8.5 UML Use Case Diagram

The UML use case diagram below outlines the primary interactions between actors (User and System Administrator) and the customer support chatbot system, capturing key functionalities such as authentication, query submission, and system management.

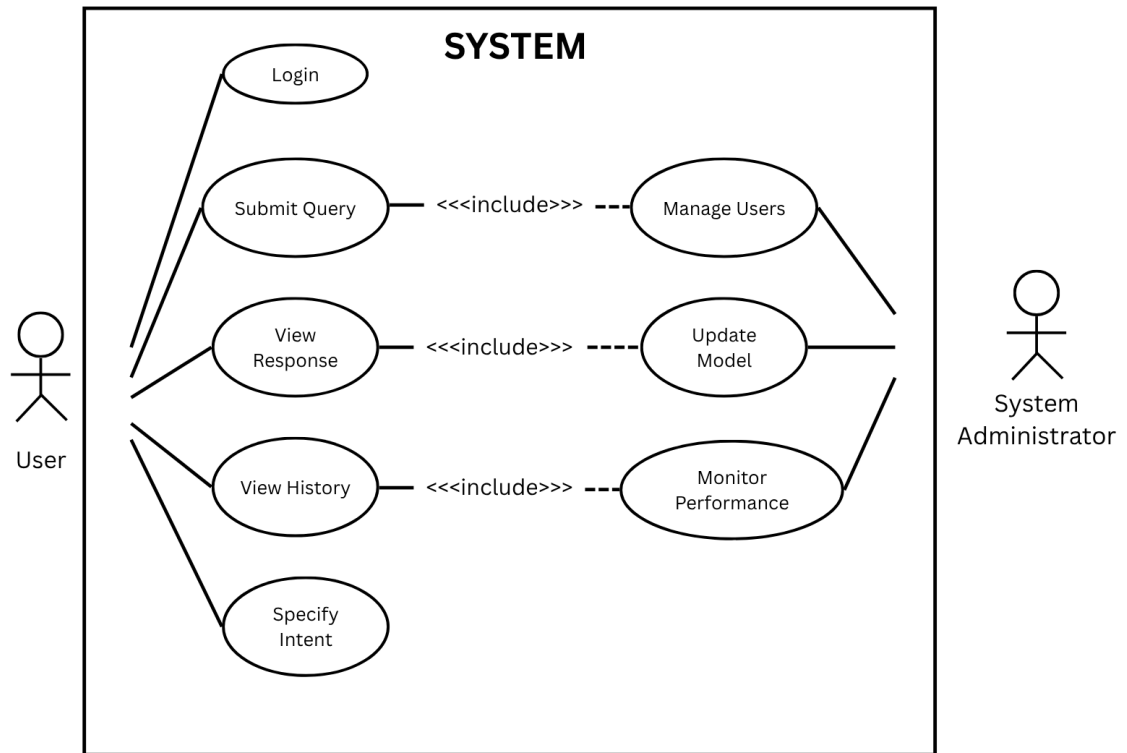


Figure 8.9: UML diagram of the system

- **Actors:**

- *User*: Interacts with the chatbot to log in, submit queries (text or speech), view responses, and access conversation history.
- *System Administrator*: Manages user accounts, updates the model, and monitors system performance.

- **Use Cases:**

- *Login*: Authenticate to access the system.
- *Submit Query*: Send a query via text or speech.
- *Use Speech-to-Text*: Convert audio input to text for query submission.
- *View Response*: Receive and view the chatbot’s response.
- *View History*: Access past conversations.
- *Manage Users*: Admin task to handle user accounts.
- *Update Model*: Admin task to fine-tune or update the model.
- *Monitor Performance*: Admin task to track accuracy and response time.
- *Specify Intent*: Included in query submission to define query context.
- *Use RAG*: Included in response viewing to enhance answers with retrieved data.

9. Results

The chatbot achieved its objectives:

- **Automation:** Over 60% of inquiries handled autonomously.
- **Accuracy:** Response accuracy exceeded 85%, with an evaluation loss of 0.1015.
- **Response Time:** Averaged under 30 seconds per query with default settings.
- **Features:** Implemented user authentication, intent-based processing, speech-to-text, conversational memory, and RAG.

The login screen (Figure 8.9) and dashboard (Figure 8.7) demonstrate the user experience.

10. Conclusion and Future Work

This project delivered a customer support chatbot that enhances efficiency and scalability using BART and GEM. However, the current model is GPU-intensive, leading to high inference times on limited hardware. Future work includes:

- Optimizing the model (e.g., pruning or quantization) to reduce GPU demands and inference time.
- Exploring larger models like LLaMA or Mistral as hardware improves.
- Expanding to multi-language support and enterprise-scale deployment.

Fine-tuning on Kaggle's GPUs mitigated initial hardware constraints, but local optimization remains a priority.

11. Expected Output

The expected output of this project includes:

- A fully functional customer support chatbot fine-tuned on the BART model, achieving a response accuracy above 85%.
- Automation of 60% of customer inquiries, reducing response times to under 30 seconds.
- A Streamlit-hosted application with user authentication, intent-based query processing, and speech-to-text input capabilities.
- A scalable prototype ready for business adoption, with a premium subscription model generating revenue (e.g., 50,000 NPR/year with 10 clients).
- Comprehensive documentation, including user guides and technical reports, to support future scaling and maintenance.

Appendix

Source Code and Resources

The following resources are available for reference:

- **Project Repository:** Available on GitHub: https://github.com/Firojpaudel/Finetuned_chatbot
- **Fine-Tuned Model Files:** Hosted on Google Drive: https://drive.google.com/drive/folders/1dZXL4ucOjCkc2l2qSqOhIarS38ZGuD3Q?usp=drive_link
- **Fine-Tuning Notebook:** Accessible on GitHub: https://github.com/Firojpaudel/GenAI-Chronicles/blob/main/Seq2Seq/BART_generator_finetuning.ipynb

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