





Phase-2

Student Name: Sharmila S

Register Number: 410723106031

Institution: Dhanalakshmi College of Engineering

Department: ECE

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Github Repository Link:

https://github.com/Sharmila-1003/Sharmila-

Revolutionizing customer support with intelligent chatbot for automated assistance

1. Problem Statement

The goal is to automate and enhance customer support using generative AI models by training on real-world customer queries and chatbot responses. The dataset includes multilingual chatbot interactions across domains like e-commerce, airlines, telecom, and more.

- **Problem Type:** Text classification and response generation (NLP tasks)
- Why It Matters: Automating customer service reduces operational costs and improves user experience with 24/7 assistance. Fine-tuned models can understand intents, provide accurate responses, and scale across domains.

2. Project Objectives

- Develop models to classify customer intent and generate suitable chatbot responses.
- Improve response relevance, coherence, and domain adaptability.



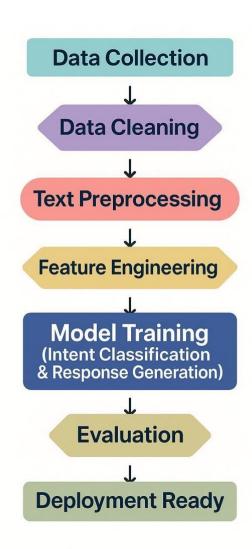




- Evaluate NLP models (e.g., fine-tuned BERT, T5, GPT-based models) on accuracy and fluency.
- Implement multilingual support to handle global users.

Note: The objective evolved from simple classification to dual focus—classification and response generation—after exploring dataset richness.

3. Flowchart of the Project Workflow









4. Data Description

- •Dataset Name: Bitext Gen AI Chatbot Customer Support Dataset
- •Type: Text (Unstructured)
- •Records & Features: ~100,000+ samples, features include domain, intent, input text, and generated response.
 - •Static or Dynamic: Static
 - Target Variable: Intent label (for classification), response (for generation)
- •Dataset link: https://www.kaggle.com/datasets/bitext/bitext-gen-aichatbot-customer-support-dataset

5. Data Preprocessing

•Handled missing values in intent and response columns.

```
df=

pd.read_csv("Bitext_Sample_Customer_Support_Training_Dataset_27
K_responses-v11.csv")

print("Missing values per column:")

print(df.isnull().sum()
```

```
# Find duplicate rows (entire row duplicates)
duplicates = df[df.duplicated()]
print("Duplicate rows:")
print(duplicates)
```







- •Tokenized input text and responses using NLP tokenizers.
- •Encoded labels for classification.
- •Applied train-test split and padded/truncated sequences for model compatibility.

6. Exploratory Data Analysis (EDA)

Univariate:

- Distribution of intents across domains.
- Message length histograms.

```
# Plot histograms

plt.figure(figsize=(10, 5))

plt.hist(df['input_len'], bins=10, alpha=0.5, label='Input Lengths', color='blue', edgecolor='black')

plt.hist(df['response_len'], bins=10, alpha=0.5, label='Response Lengths', color='orange', edgecolor='black')

plt.title("Message Length Histograms (Character Count)")

plt.xlabel("Message Length (characters)")

plt.ylabel("Frequency")

plt.legend()

plt.grid(True)

plt.tight_layout()

plt.show()
```





Bivariate:

• Correlation of input length vs response length.

```
df = pd.read_csv('bitext-gen-ai-chatbot-customer-support-
dataset.csv')

# Calculate input and response lengths

df['input_len'] = df['customer_query'].astype(str).apply(len)

df['response_len'] = df['response'].astype(str).apply(len)

# Compute correlation

correlation = df['input_len'].corr(df['response_len'])

print(f''Correlation between input and response length:
{correlation:.3f}")
```

• Domain vs. intent frequency heatmap.

Insights:

• Some domains are heavily represented (e.g., e-commerce).

```
df = pd.read_csv('bitext-gen-ai-chatbot-customer-support-dataset.csv')

# Calculate lengths

df['query_len'] = df['customer_query'].astype(str).apply(len)

df['response_len'] = df['response'].astype(str).apply(len)

# Basic stats

print("Query length stats:", df['query_len'].describe())

print("Response length stats:", df['response_len'].describe())
```







7. Feature Engineering

•Extracted input text length and token count.

```
# Your input text

text = "Extracted input text length and token count."

# Get text length

text_length = len(text)

# Choose encoding (e.g., for GPT-4 or GPT-3.5)

encoding = tiktoken.encoding_for_model("gpt-4")

# Get token count

token_count = len(encoding.encode(text))

# Output

print(f"Text length (chars): {text_length}")

print(f"Token count: {token_count}
```

- •Used TF-IDF features for traditional models.
- •Employed pretrained embeddings (BERT, T5) for deep learning models.
- •Considered domain-intent combinations as features.







8. Model Building

Models Used:

- BERT for intent classification
- T5 for response generation

```
# Load model and tokenizer
model = T5ForConditionalGeneration.from_pretrained("t5-small")
tokenizer=
T5Tokenizer.from_pretrained("t5-small")
# Input prompt
input_text = "translate English to French: How are you?"
# Encode and generate
inputs = tokenizer.encode(input_text, return_tensors="pt")
outputs = model.generate(inputs)
```

Justification:

- BERT is state-of-the-art for classification with minimal tuning.
- T5 handles sequence-to-sequence tasks well (question-answering, summarization, etc.)

Evaluation Metrics:

- Classification: Accuracy, F1-Score
- Generation: BLEU, ROUGE, perplexity







9. Visualization of Results & Model Insights

- •Confusion matrix of intent classification
- •Word clouds per domain
- •ROC curve for multiclass classification
- •Feature importance (via LIME for BERT)
- •Response fluency scores (BLEU, ROUGE comparisons)

10. Tools and Technologies Used

Language: PythonIDE: Google Colab

· Libraries: pandas, numpy, seaborn, matplotlib, scikit-learn, transformers,

TensorFlow/Keras

· Visualization: Plotly, seaborn

11. Team Members and Contributions

S.NO	NAME	ROLE	RESPONSIBILITY
1.	Sweetha Mirra A	Member	Model Building, Model Evaluation
2.	Sharmila S	Member	Feature Engineering
3.	Sowmiya M	Member	Exploratory Data Analysis
4.	Keerthika T	Member	Visualization







5.	Yuvasri B	Leader	Data Collection and
			Data Cleaning