

BankBot AI



Chatbot Smart Conversational Banking System

Milestone 1+Milestone 2 Milestone 3+Milestone 4

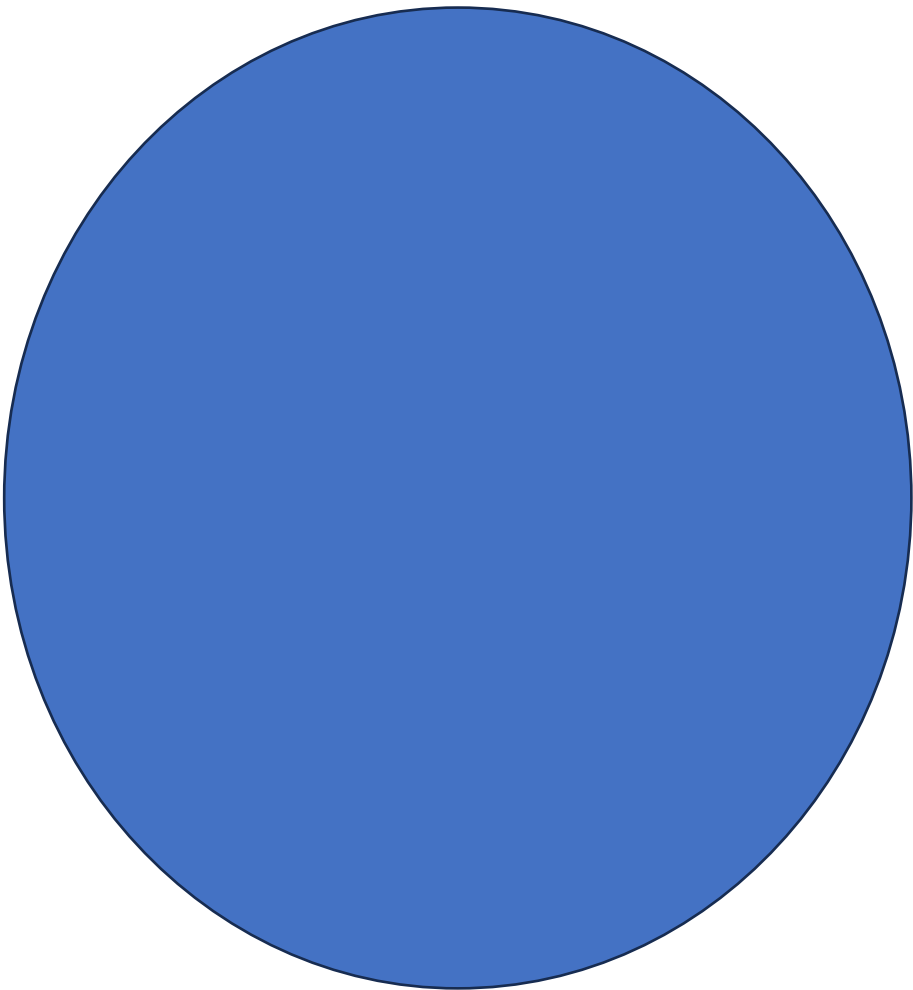
Problem :

Customers often have recurring banking queries related to account balance, interest rates, loan eligibility, transaction status, branch details, etc. Relying on manual customer service teams leads

to delays and high operational costs. This project aims to build an intelligent chatbot that can handle these questions through natural conversations. It will support both rule-based and machine learning approaches to ensure accuracy and scalability. The chatbot will be accessible via web interface and possibly integrated into mobile apps or WhatsApp.

Milestone 1

- This is mainly revolve around finding entity and intent recognition .
- Handles intents like balance check, loan inquiry, card blocking, branch locator, and more.
- Interference using streamlit .
- Backend using SQLite .
-
-



Train Model

Epochs
3 - +

Batch size
8 - +

Learning rate
0.000020 - +

Start training

Model trained successfully

Start Training

BankBot — Intent + Entity Demo

Intents (edit s add)

› check_balance (23 examples)

› transfer_money (21 examples)

› card_block (23 examples)

› find_atm (23 examples)

Demo — Intent & Entity

Enter user query

Predict

Quick test

Run sample tests

NLU Inference

Enter user query

-
-

Milestone 2:

- This is Ai powered chatbot , which uses grog api and streamlit , llm , etc for the interactive interface

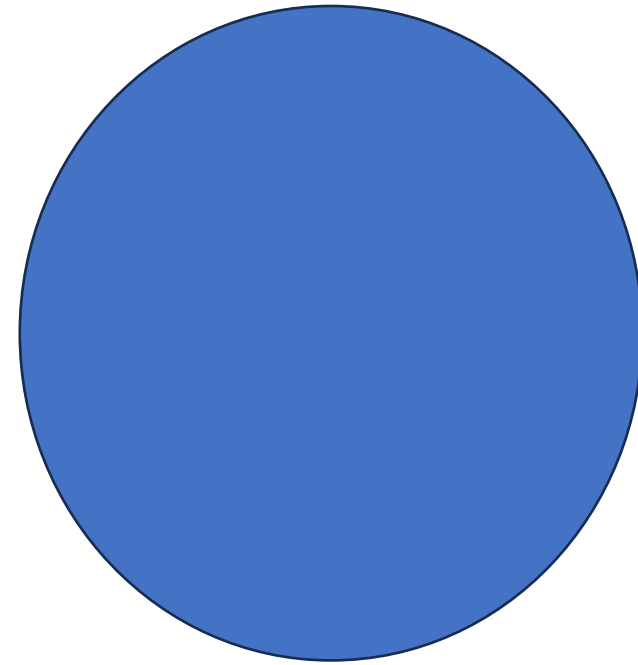
- This has a responsive UI with option to create user , login the with the same account
- And there is Chatbot Which is capable to tell details 1)about user ,
2) type of card ,
3)amount in account ,
4)transaction between various user
- This also maintain a Database in the backend using SQLite which contain
1)user name ,
2)password(encrypted form) ,
3)type of account ,

4)transaction,
5)amount in account

Problem :

- 1) Traditional banking systems: · 2)Time-consuming manual processes · 3)Limited working hours
4)No instant account support 5)Difficult for non-technical users

Output:



[main app](#)[Chatbot](#)[Create Account](#)[Login](#)

AI Banking Chatbot

 Type Here

Send



Deploy

main app
Chatbot
Create Account
Login

Create New Bank Account

Create Account

Milestone 3:

- Milestone is an extended version of the milestone 2 , milestone 2 can Answer only question related to transfer, cards , account but the milestone 3 can answer the general question , question of the various field mainly
- This use Technology such as Groq api , local llm ,

- This also uses local llm
- This is Domain-aware AI chatbot now earlier it was simple Q&A bot
- LLM generic answer

Problem Faced :

- Simple Q&A bot vs Domain-aware chatbot difference
- Current project me **exact problems**
- llm_local.py & llm_gorg.py ke context me issue
- Missing **domain classification & routing logic**
- Clean **architecture explanation**

Technology Used:

1. LLM Local (llm_local.py)

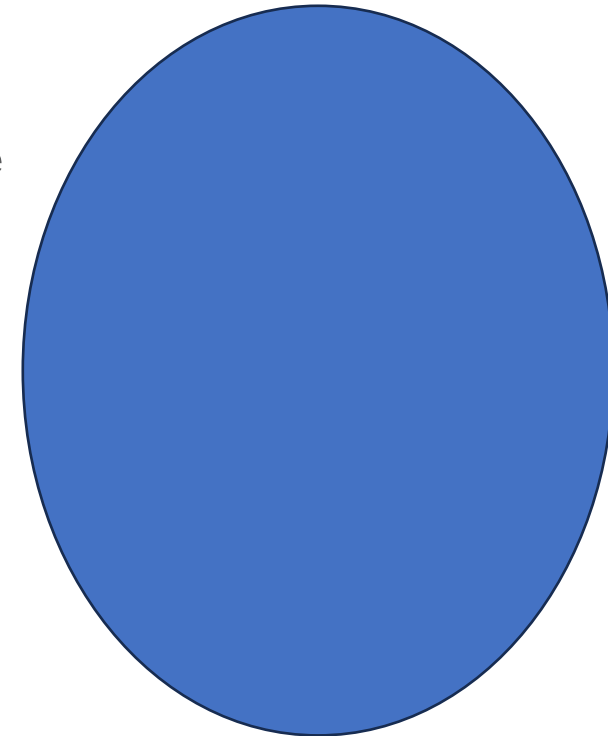
Definition:

LLM Local is a **domain-specific intelligence layer** designed to answer questions using **local and structured data sources**.

Data Sources

- Local databases (MySQL / SQLite)
- CSV files (e.g., iris.csv)
- Internal project-specific data

How it Works



- The user query is processed against local data
- Responses are generated using database queries, embeddings, or rule-based logic · It does not rely on external APIs or internet-based knowledge

Strengths

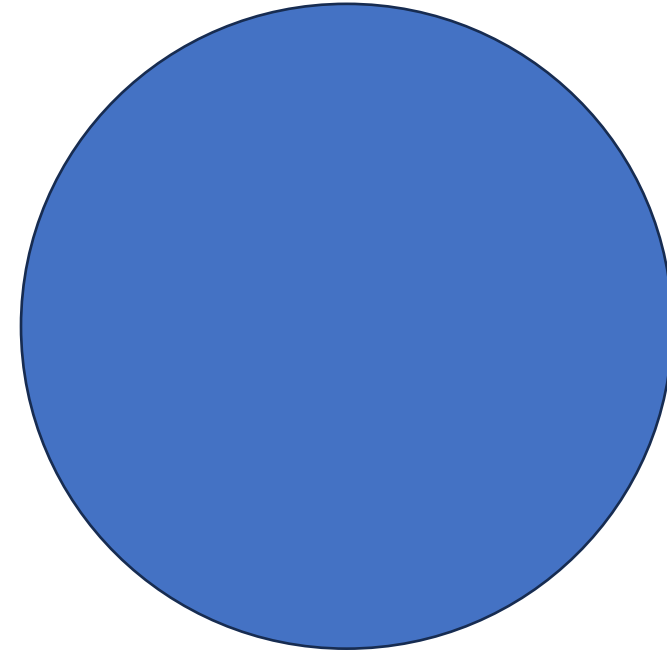
- High accuracy for internal data
- Fast response time
- Data privacy and security
- Ideal for banking, internal tools, and structured datasets

Limitations

- Cannot answer questions outside the available data
- Not suitable for general AI/ML theory or conceptual explanations

Example Queries

- “What is the balance of a customer?”
- “How many features are in the Iris dataset?”
- “Show the last transaction details”



2. LLM Groq / General LLM (llm_gorg.py)

Definition:

LLM Groq is a **general-purpose language model** used for answering **theoretical and conceptual questions** related to domains like Data Science, Machine Learning, and Deep Learning.

Data Source

- Pre-trained large language models (Groq / GPT / HuggingFace)
- Trained on large-scale, general-purpose data

How it Works

- Understands the semantic meaning of the question
- Generates explanations using reasoning and language understanding ·

Does not depend on local project data

Strengths

- Explains complex concepts clearly
- Handles unseen and open-ended questions

- Suitable for learning, theory, and comparisons

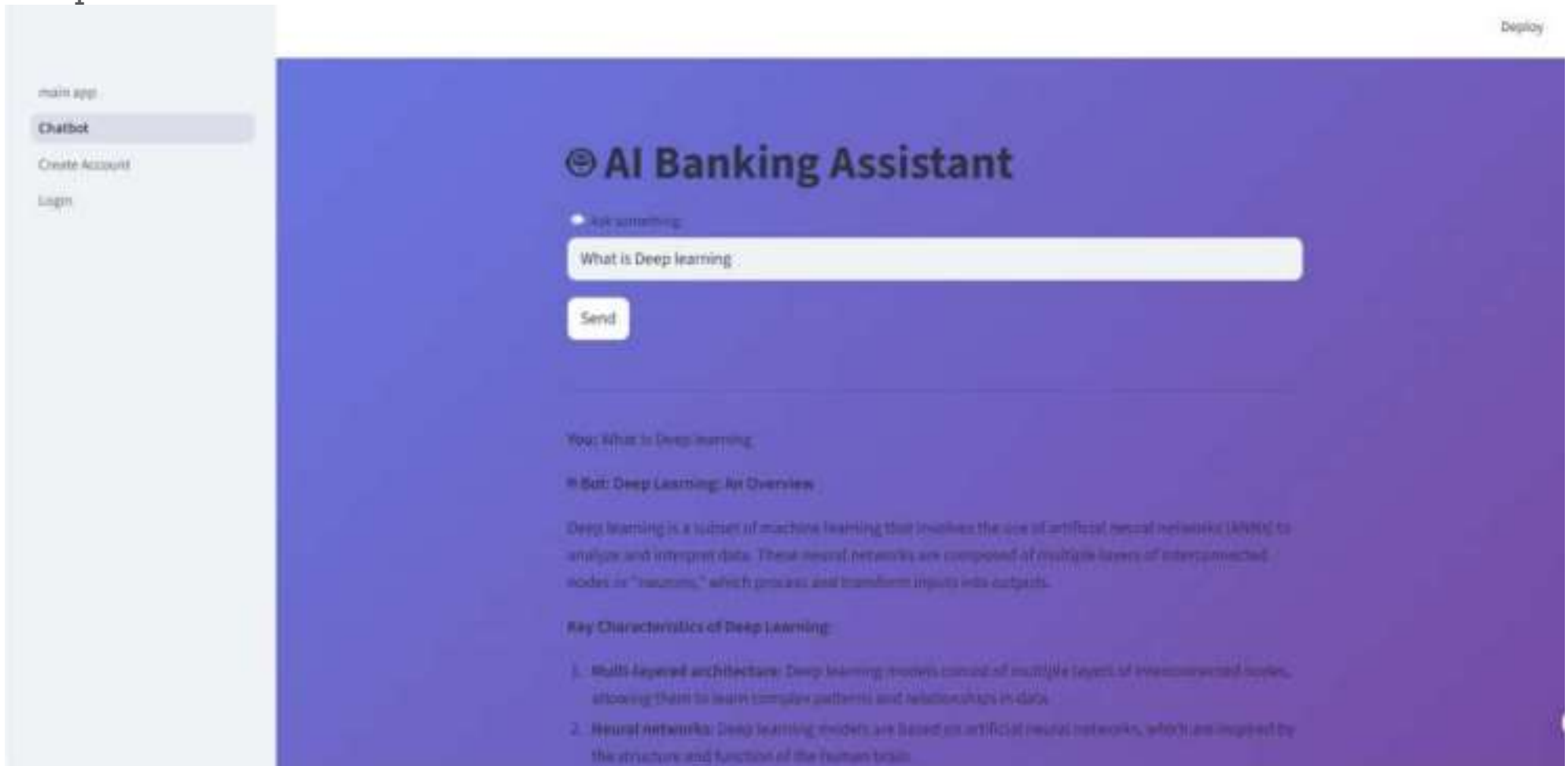
Limitations

- Answers can be generic
- May produce hallucinated responses
- No access to internal databases

Example Queries

- “What is backpropagation in neural networks?”
- “Difference between supervised and unsupervised learning”
- “Explain overfitting with an example”

Output:



Milestone 4:

So the milestone four revolves around taking user intent query and then classifying the same based the on the intent as

- 1)Transfer money ,
- 2)Card block ,
- 3)Find Atm
- 4)Check balance

To obtain pie chat based on the queries comparison , could be better understood by output.

This has an option to count the type of the question based on the query and can also export the question count list as per the requirement

Editorial could also be trained .

We can export the file.

Technology Used:

- Python
- LangChain
- Groq LLM
- Local LLaMA (GGUF)
- SQLite
- Streamlit

Problem Faced:

Intent Misclassification

Some user queries were ambiguous and matched multiple intents, which led to incorrect classification, especially when queries contained overlapping keywords.

Confidence Score Variations

Similar queries sometimes produced different confidence scores, making it challenging to define a fixed threshold for accurate intent detection.

Limited Training Data

Initial training examples were limited, which affected the accuracy of intent prediction and required frequent updates to the editorial/training data.

Visualization Handling

Managing pie chart and bar chart rendering dynamically in Streamlit based on user selection required careful state and layout handling.

Performance Issues with Local LLaMA

Running the GGUF-based local LLaMA model resulted in higher latency compared to cloud-based models, especially during repeated query analysis.

Data Persistence and Logging

Maintaining consistent query logs in SQLite and syncing them with real-time analytics dashboards required additional handling.

Model Switching Complexity

Supporting both Groq LLM and local LLaMA increased complexity in configuration and response standardization.

AI Banking Assistant

- Go to
- ☐ Chatbot
 - ☒ Admin Analytics
 - ☐ Logout

BankBot Admin

- Navigation
- ☒ Chat Analytics
 - ☐ Query Analytics
 - ☐ Training Editor
 - ☐ Export Logs

Test Query

Enter user query

how are you

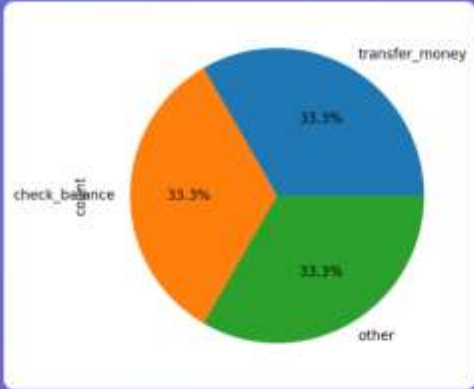
Analyze Query



Chat Analytics

Select intent

- ☒ overall ☐ check_balance ☐ transfer_money ☐ card_block ☐ find_atm



	question	intent	timestamp
0	transfer 100	transfer_money	2026-01-11 23
1	check my acc	check_balance	2026-01-11 23
2	how are you	other	2026-01-11 23

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Test Query

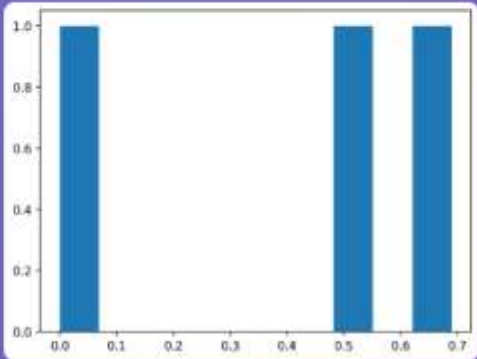
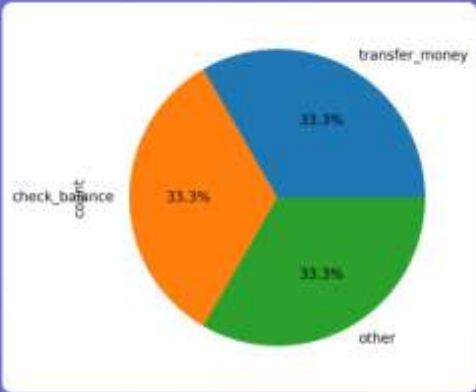
Enter user query

how are you

Analyze Query



Query Analytics



	question	intent	confidence	timestamp
2	how are you	other	0	2026-01-11 23:24:39
1	check my account	check_balance	0.5	2026-01-11 23:24:32
0	transfer 100	transfer_money	0.69	2026-01-11 23:23:19

Thank You 