

AI-POWERED MOBILE APPLICATION FOR BREATHING SOUND ANALYSIS AND DISEASE DETECTION

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PLAN



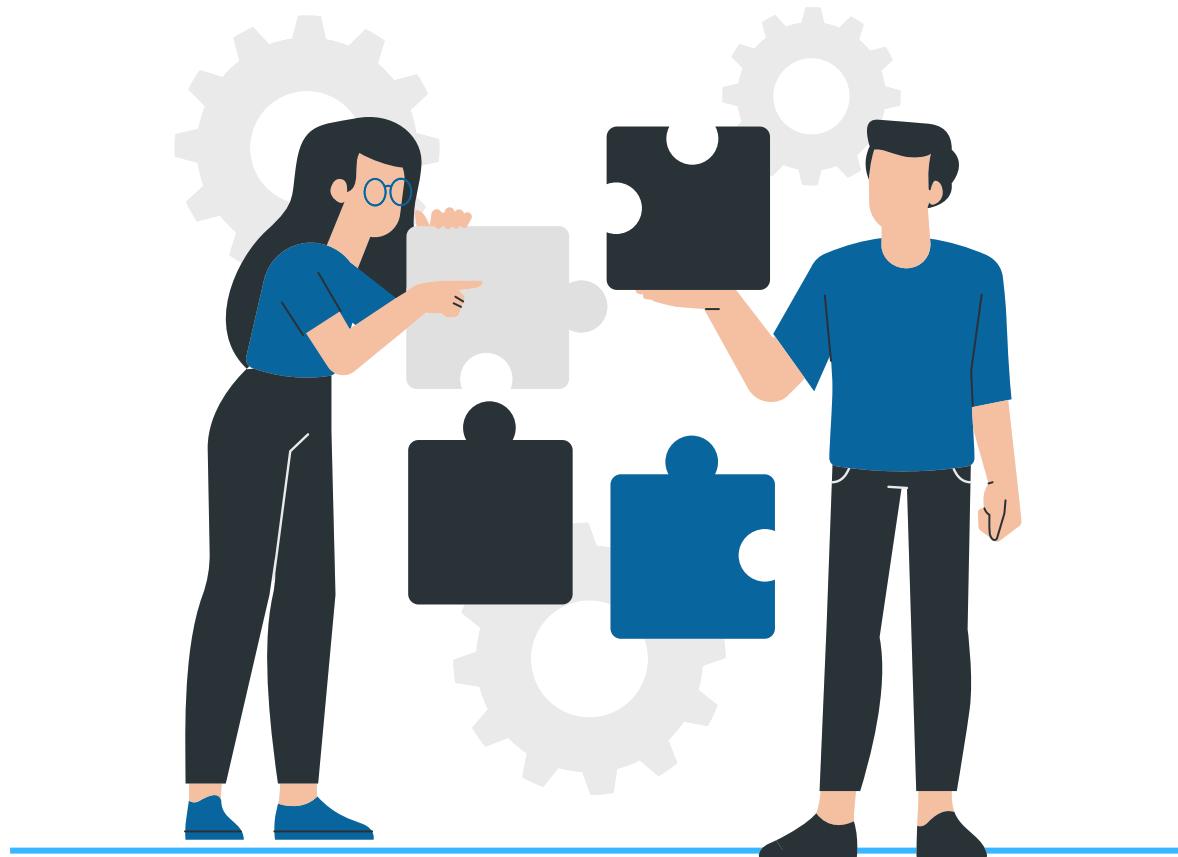
1. Introduction

2. Technical Approach

3. Limitations & Perspectives

4. Demo & Conclusion

CONTEXT & MOTIVATION



“

“ The greatest wealth is health, yet millions still lack access to basic diagnosis. ”

The World Health Organization

PROBLEMS & SOLUTION

- Manual auscultation is subjective & skill-dependent
- Existing tools focus only on sound, ignore context
- Lack of explainability in predictions
- Limited access outside hospitals or clinics

- AI-powered mobile app for recording and analyzing breathing
- Multimodal analysis: audio + clinical documents
- Clear, explainable feedback with a conversational AI assistant
- Fully accessible via smartphone, secure & privacy-focused



METHODOLOGY

CRISP-DM

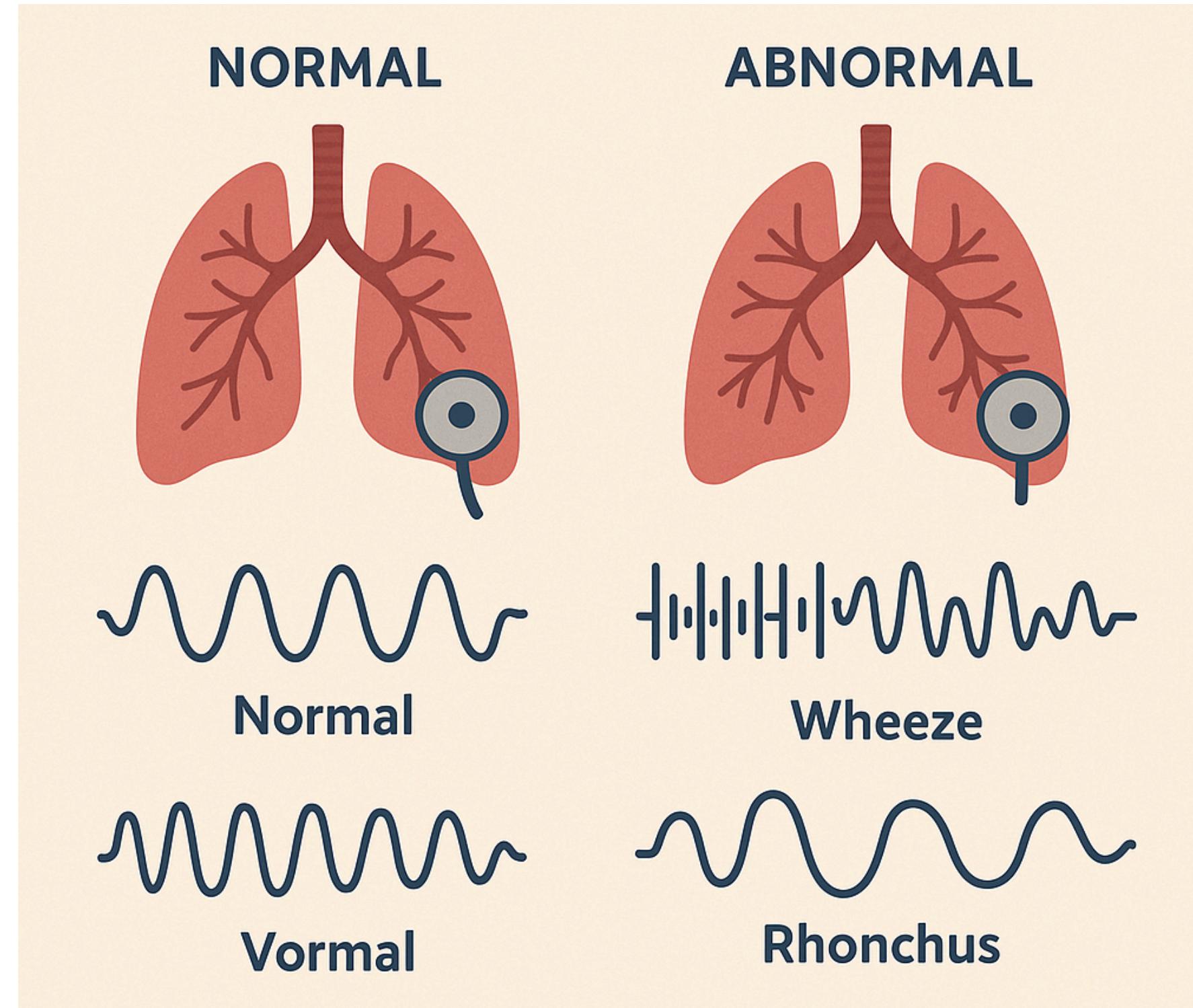
1. Business Understanding
2. Data Understanding & Preparation
3. Modeling

4. Evaluation

5. Deployment



RESPIRATORY SOUND CLASSIFICATION



DATASET

**ICBHI 2017
Respiratory
Sound Dataset**

**5.5 hours of lung sounds
from 126 patients**

MODELING APPROACH

CLAP Processor

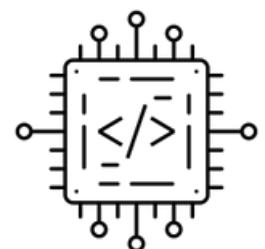


Lung Audio



Patient Text

Embedding



CLASSIFIER TASK

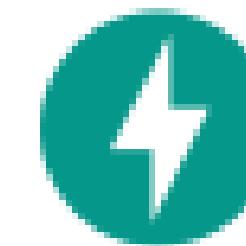
 **NORMAL**

XWHEEZE

XCRACKLE

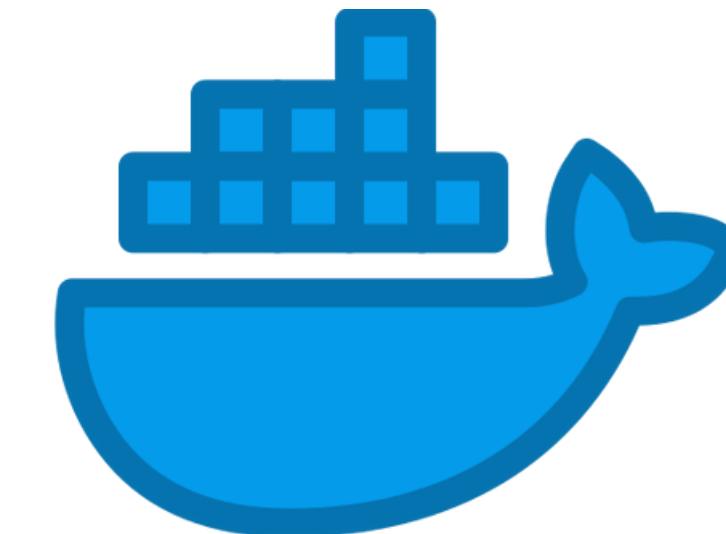
DEPLOYMENT

Built with FastAPI



FastAPI

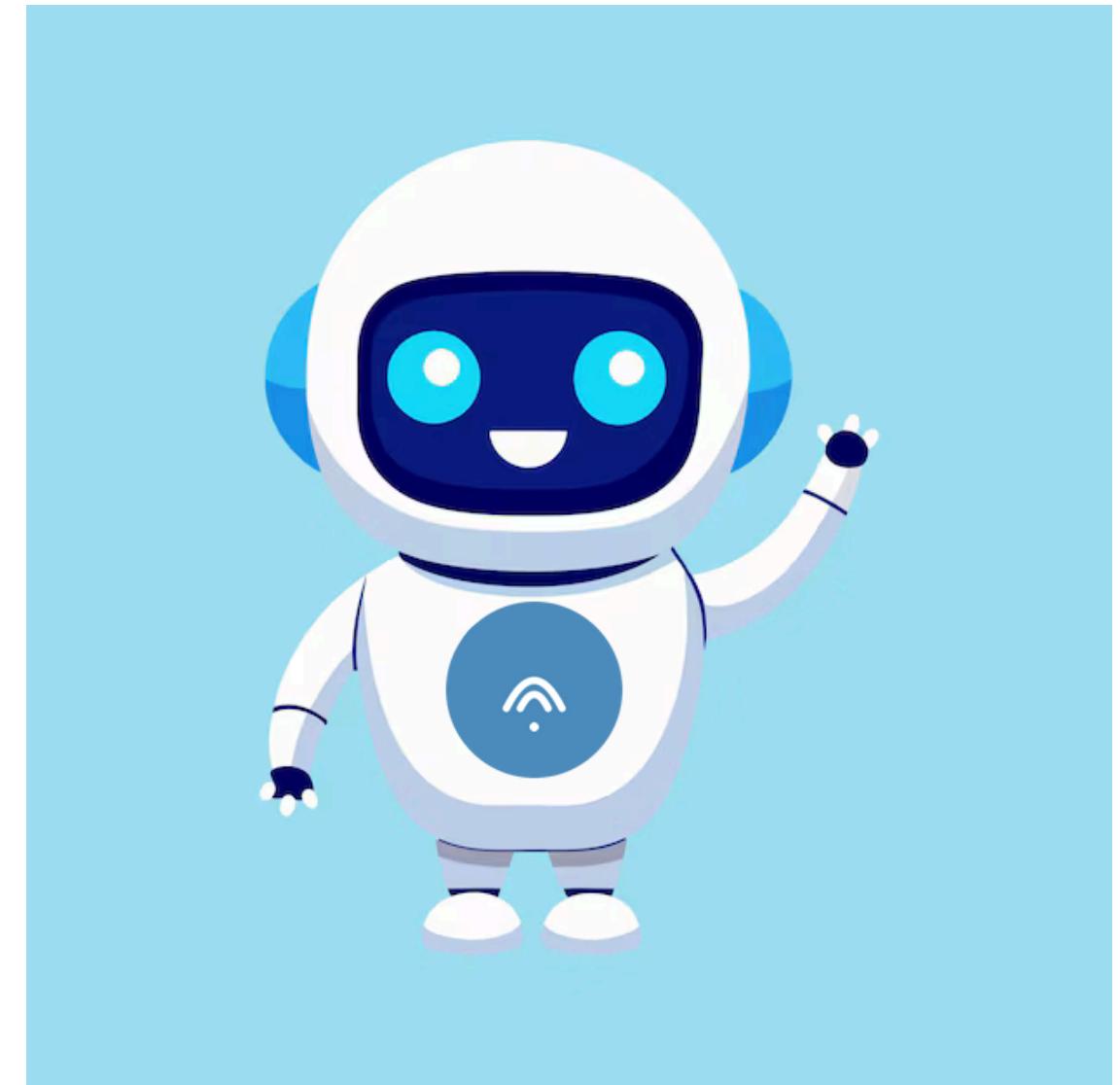
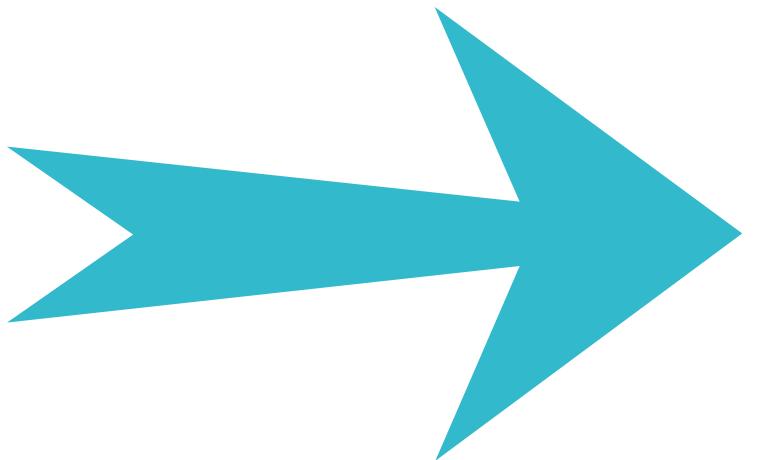
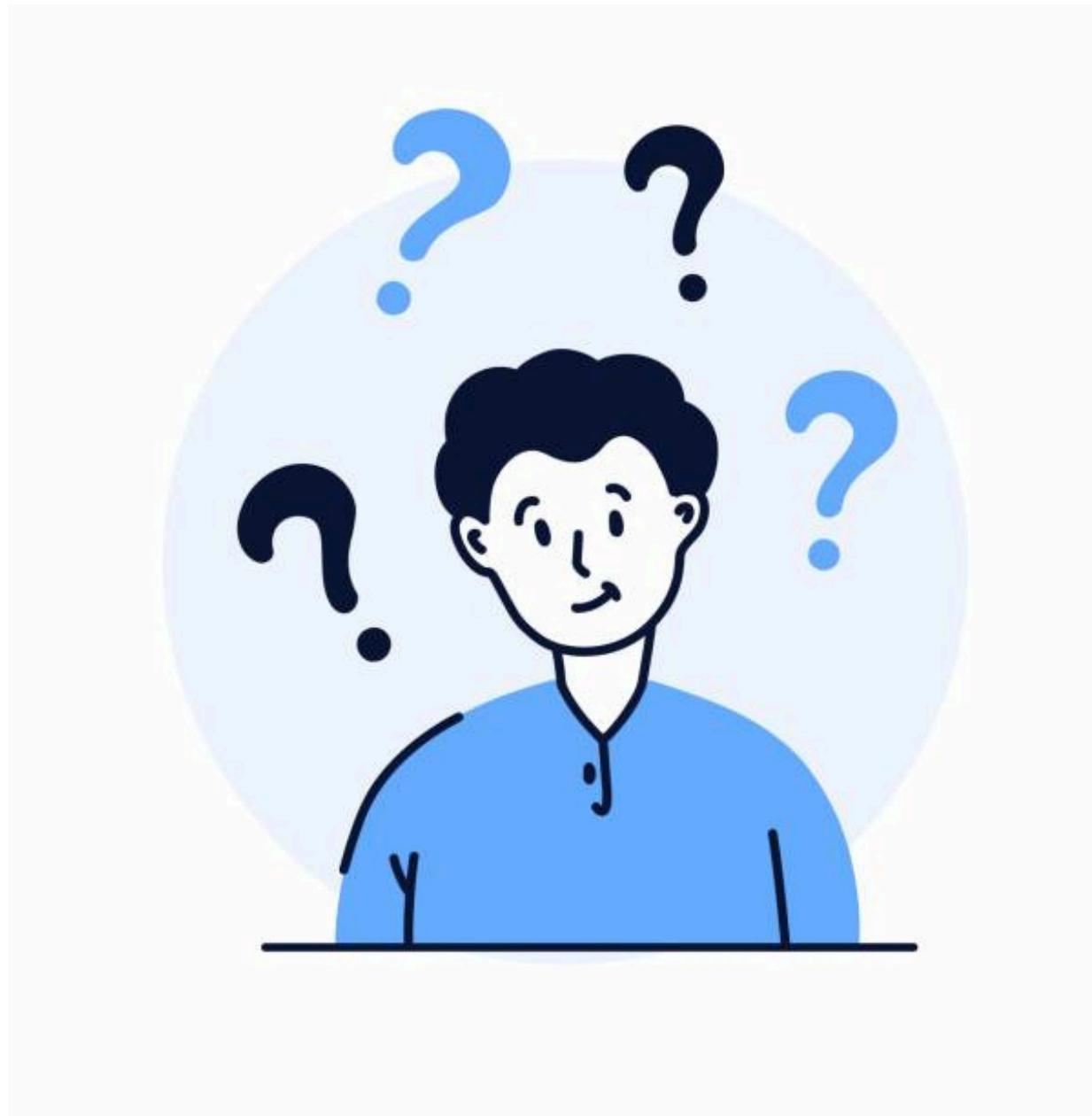
Packaged & containerized
using Docker



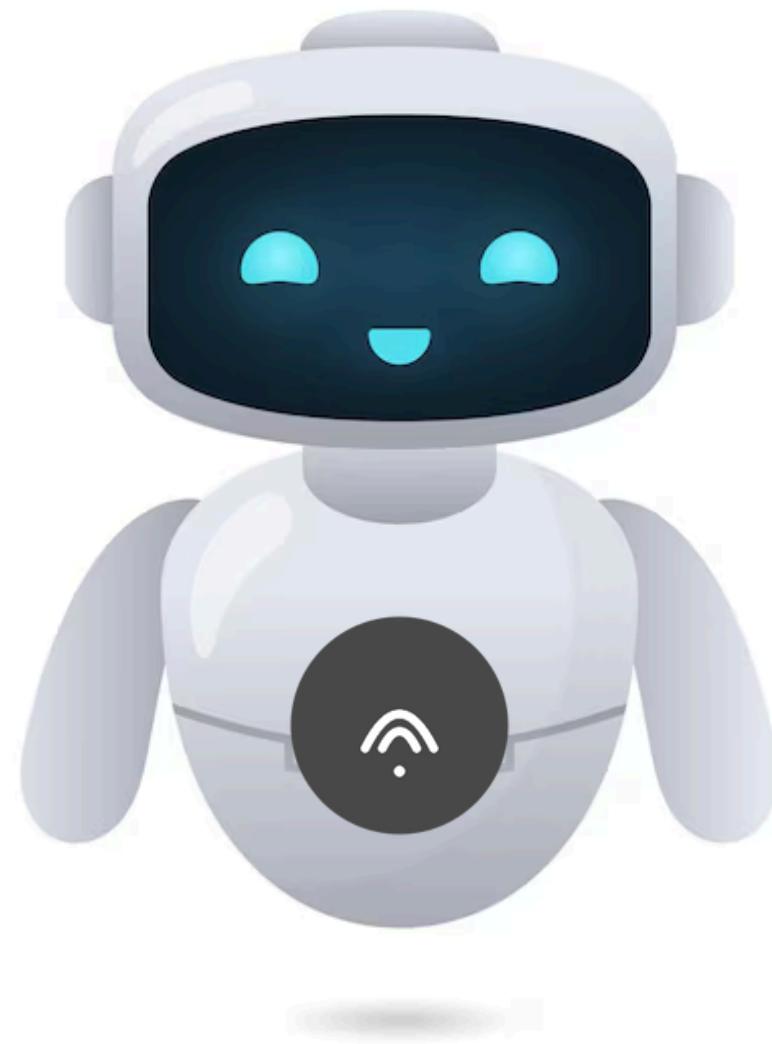
Ready for real-time
inference via REST API



WHY WE BUILT AN AI ASSISTANT



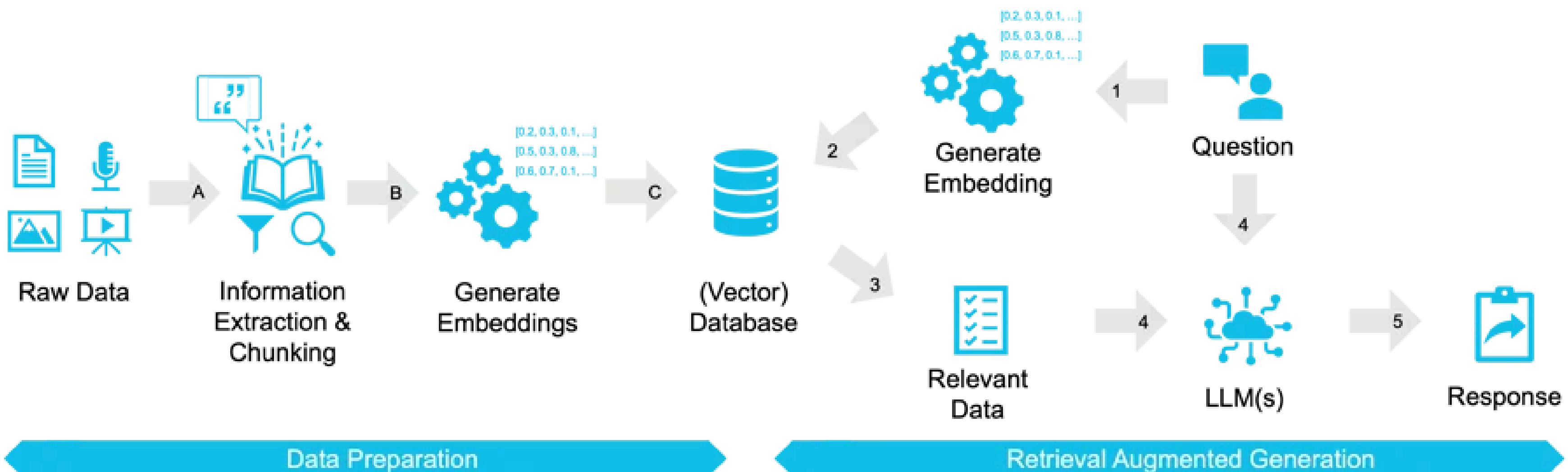
WHAT THE AI ASSISTANT AIMS TO ACHIEVE



- Provide clear and understandable explanations of medical terms**
- Answer health-related questions based on the user's symptoms.**
- Guide users about what actions to consider next (e.g., seeing a doctor, monitoring symptoms).**
- Work offline, so that users have access to it anytime.**

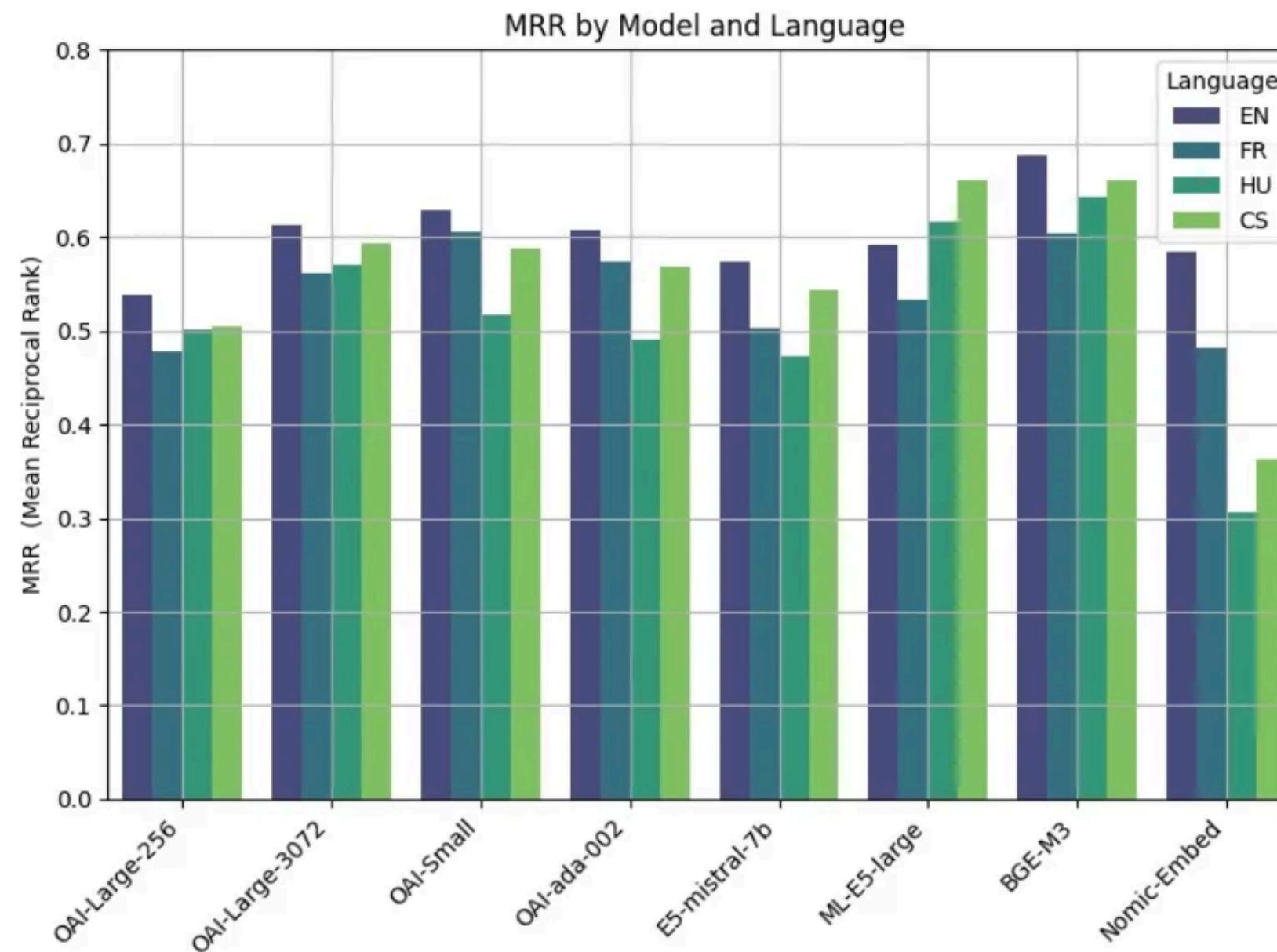
Designed with empathy. Powered by AI

HOW IT WORKS — TECHNICAL OVERVIEW



EVALUATING THE EMBEDDING MODEL

Because good answers start with good context

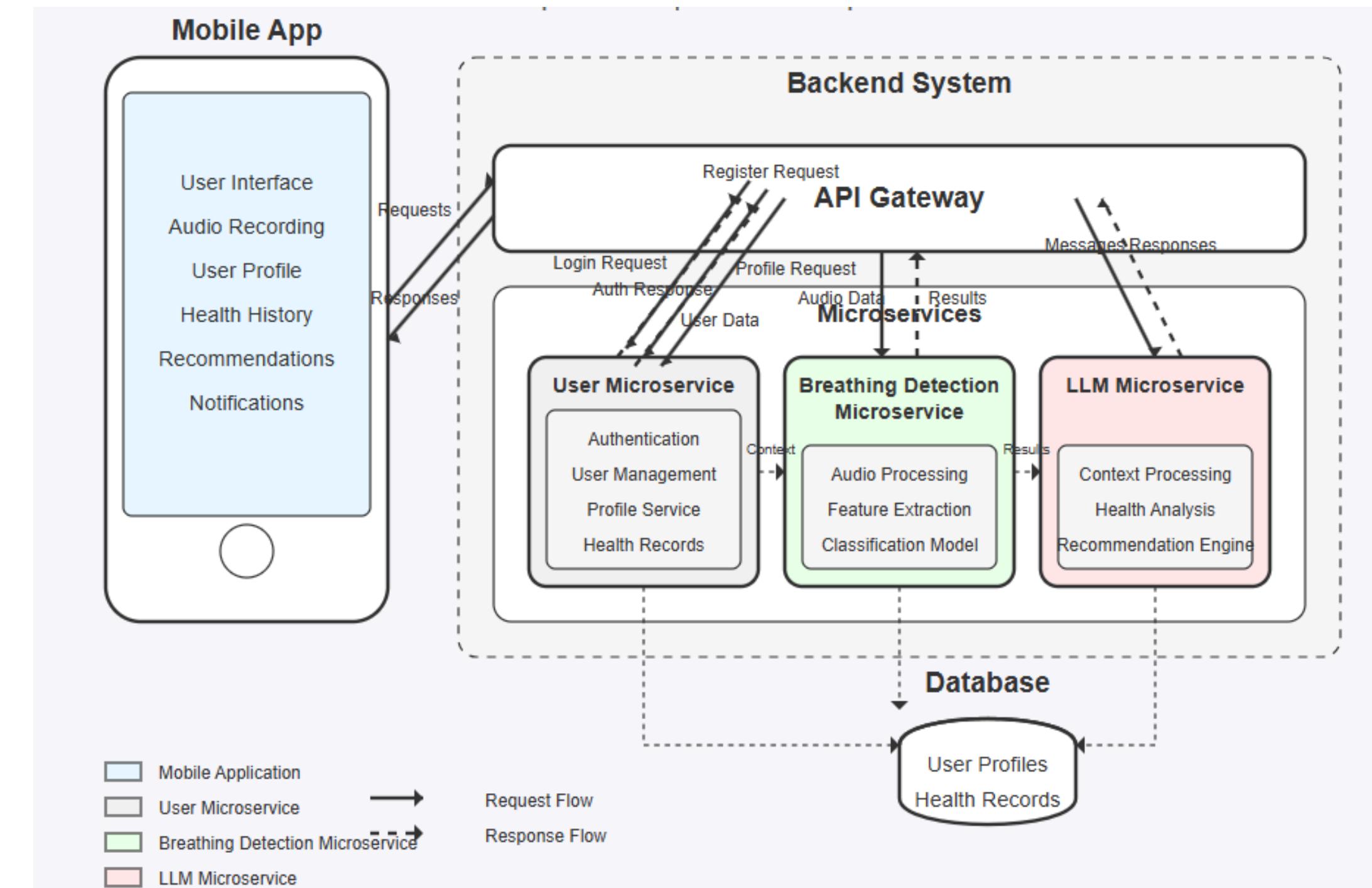


RAG VS. LLM ALONE

Does retrieval improve user support? Let's compare.

Metric	RAG System	Baseline
Groundedness	8.7	5.2
Correctness	8.5	5.5
Coherence	9.1	8.7
Relevance	8.9	6.3
Novelty	7.8	6.9
Overall Score	8.6	6.4

FULL SYSTEM ARCHITECTURE



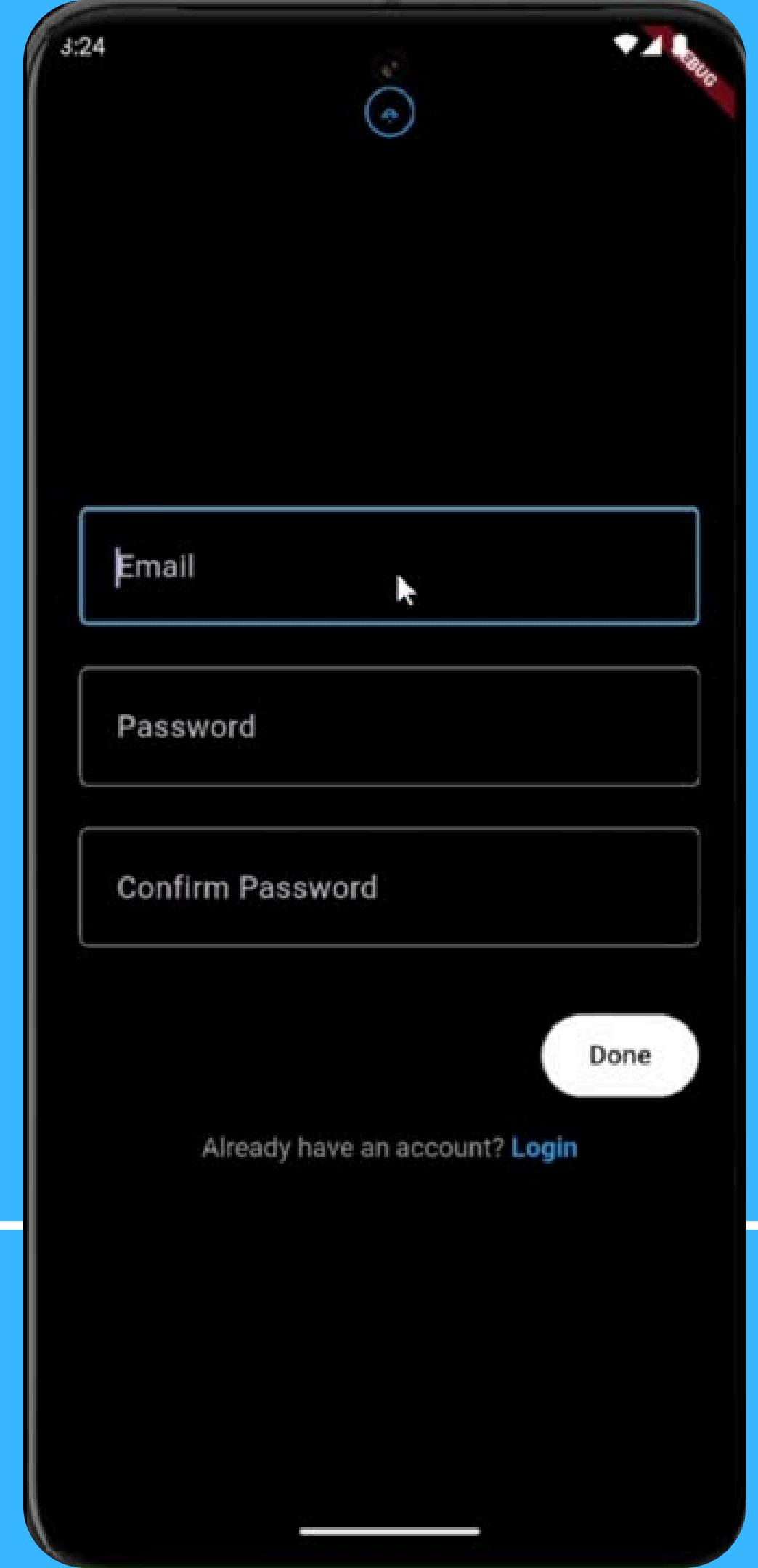
LIMITATIONS & PERSPECTIVES

- ✖ Limited Dataset Diversity
- ✖ Imperfect Audio Quality
- ✖ LLM Hallucinations
- ✖ Lack of Real Clinical Validation

- 🚀 Larger & More Diverse Audio Dataset
- 🚀 Fine-Tuning the Classifier
- 🚀 Enhanced RAG Pipeline
- 🚀 Clinical Collaboration



▶ DEMO



CONCLUSION

- ✓ Developed a complete, end-to-end AI system for respiratory health
- ⌚ Combines detection (classification) and explanation (assistant) in one platform
- 📱 Designed for accessibility on real-world mobile or edge devices
- 🧠 Contributes to the future of smart, explainable healthcare



**THANK YOU
FOR YOUR ATTENTION !**

**DO YOU HAVE ANY
QUESTIONS?**

