

Perfect — with **Streamlit confirmed as the frontend**, and hosting included — here is your **finalized Developer-Focused Blueprint Document**. This version is structured and ready to be exported as a PDF after your review.

Blueprint Document: AI-Powered Diabetes Risk Prediction System

1. **Project Overview**

This is an end-to-end ML application that predicts diabetes risk using the Pima Indians Diabetes Dataset. The system includes data preprocessing, model training, explainability, a REST API, and a web-based **Streamlit frontend**, all deployable on the cloud.

2. **Goals & Objectives**

Goals:

- Accurately predict diabetes risk.
- Build an explainable, web-accessible AI solution.
- Deliver a complete full-stack AI application using APIs and a UI.

Objectives:

- Train and evaluate ML models.
 - Implement SHAP-based model explainability.
 - Build a REST API for predictions.
 - Develop and deploy a **Streamlit frontend** to interact with the API.
-

3. **Project Scope**

In Scope:

- Data cleaning, EDA, feature engineering
- ML model training and evaluation
- SHAP explainability integration
- REST API using FastAPI or Flask
- Streamlit frontend UI (mandatory)
- Web deployment of both API and UI

Out of Scope:

- User login/auth systems

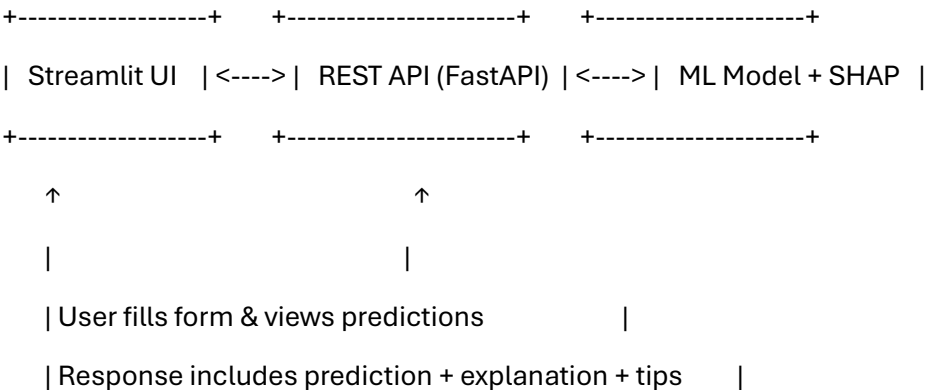
- Real-time data streams
- Multi-language or mobile app support

4. 📅 Timeline & Milestones

Phase	Description	Duration	Target Dates
Phase 1: Planning	Scope, design, setup	1 day	Day 1
Phase 2: Data Processing	EDA, cleaning, transformation	1–2 days	Day 2–3
Phase 3: Modeling	Train/test models, metrics, tuning	2 days	Day 4–5
Phase 4: Explainability	SHAP/LIME integration	1 day	Day 6
Phase 5: API Development	REST API for predictions & health tips	2 days	Day 7–8
Phase 6: Frontend UI	Build Streamlit interface	1 day	Day 9
Phase 7: Deployment	Host API + Streamlit on Render/Streamlit Cloud	1 day	Day 10
Phase 8: Final Testing	Postman tests, cleanup, README, polish	1 day	Day 11

Total Estimated Duration: 11 Days

5. 🏠 System Architecture



6. 🧰 Technology Stack

Component	Tool/Library
Language	Python 3.10+

Component	Tool/Library
ML Libraries	scikit-learn, XGBoost, SHAP
API Framework	FastAPI or Flask
UI	Streamlit
Visualization	Matplotlib, Seaborn
Deployment	Render, Streamlit Cloud
Testing	pytest, Postman
Version Control	Git + GitHub

7. ML Workflow

1. Load and clean dataset
 2. Handle zero or missing values
 3. Normalize/scale features
 4. Train multiple models (LogReg, RF, XGB)
 5. Evaluate via Accuracy, F1, ROC-AUC
 6. Save best model (joblib or pickle)
 7. Apply SHAP to explain predictions
-

8. API Design

Base URL: /api/v1

POST /predict

- **Input:** JSON with 8 patient health metrics
- **Output:** {"risk": "high", "probability": 0.84, "top_features": [...]}

GET /health-tips

- **Input:** Optional parameters (age, BMI, glucose)
- **Output:** JSON advice (e.g., "Increase fiber intake")

POST /explain

- **Input:** Same as /predict
 - **Output:** SHAP value summary
-

9. Feature List (Frozen Scope)


Feature	Status
Data preprocessing & EDA	✓
Model training & evaluation	✓
SHAP integration	✓
REST API with 3 endpoints	✓
Streamlit web interface	✓
API + UI Hosting	✓
Testing & Documentation	✓

 **No new features will be added** after this list is locked.

10. Assumptions & Constraints

- Dataset is stable and not changing
 - Model doesn't require real-time training
 - Hosting is done on free-tier platforms (limited resources)
 - UI is for demo purposes, not production-grade UX
-

11. Deliverables

- notebooks/: EDA, modeling, evaluation
 - api/: Python scripts for REST API
 - frontend/: Streamlit app
 - models/: Trained model files
 - reports/: Final PDF blueprint + optional prediction reports
 - requirements.txt: Full dependency list
 - README.md: Project overview and setup instructions
 -  Deployed App URL(s)
-

12. Deployment Plan

Component	Platform	Notes
API	Render.com	Deploy via Gunicorn + FastAPI
Frontend	Streamlit Cloud	Deploy directly from GitHub repo
Optional Bundle	Docker	Unified API + frontend (optional)

13. 🚧 Risks & Mitigation

Risk	Mitigation
SHAP performance on large data	Sample data or use summary SHAP
Streamlit load times	Optimize model load & SHAP caching
Deployment issues	Use standard deployment guides
Over-scoping	Scope locked to avoid creep

14. 🧪 Success Criteria

- Model achieves $\geq 80\%$ accuracy or ROC-AUC
 - REST API responds to all planned routes
 - Streamlit app works end-to-end with live API
 - Project is fully documented and hosted live
-

15. 🌟 Future Enhancements (Post-project Only)

- Voice input via speech-to-text
 - User authentication + session tracking
 - Expand to time-series modeling
 - Email PDF reports to users
 - Mobile responsive UI (Streamlit + CSS hacks)
-