MedPredict-X: Context-Aware Hospital Readmission Forecasting with LLM-Powered Clinical Reasoning

Sreekaran Reddy Ramasahayam , Maruthi Pabbathi , Lyza Iamrache , Vijay Bhaskar Madasu

Problem Statement

Every readmission isn't just a number it's a missed moment of care. Predictive systems flag risks but overlook the human story: a storm that delays a nurse's visit, bad air that worsens recovery, a holiday that postpones a follow-up. Hospitals don't just need prediction; they need understanding, empathy, and reasoning data that sees the human side of healthcare.

Objective

- We predict 30-day readmission risk with Logistic Regression, fusing clinical data with context (weather, PM2.5, holidays).
- And recommends follow-up based on risk tier and to which a RAG-powered reasoning explains the why behind each prediction.

Methodology

Data Collection & Preprocessing :

- We enriched the **Diabetes 130-US Hospital** dataset (100 K+ records) with **real-world context like** weather, air quality (PM 2.5), and holiday data to capture external influences.

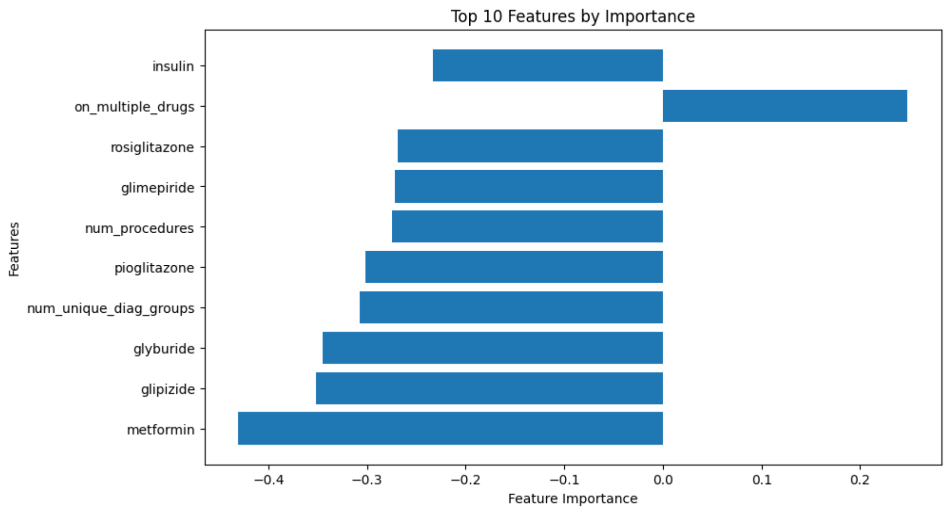
Feature Engineering :

- Categorical fields were clinically encoded for interpretability and unrealistic cases such as *expired/hospice patients marked readmitted* were removed.
- **max_glu_serum** and **A1Cresult** were numerically encoded and combined into a unified **feature** a stronger indicator of diabetic instability and readmission risk.

Train and Test Split :

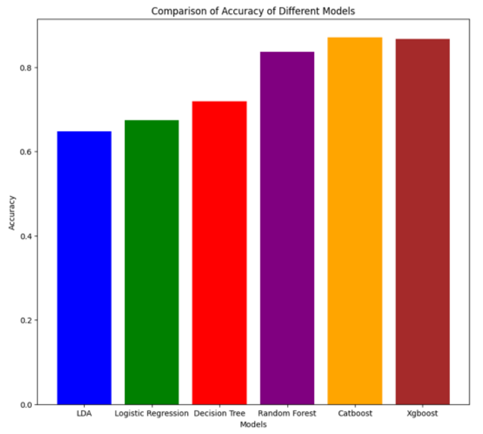
- Dataset initially showed a significant imbalance between readmitted and non-readmitted patients.
- Correcting this, **SMOTE** method was applied on the **training data** to generate realistic minority-class samples, ensuring balanced learning without biasing the test evaluation.

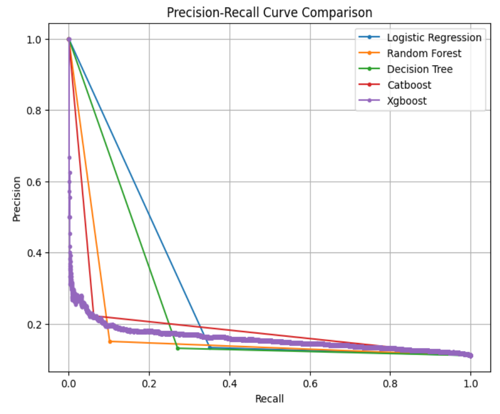
Methodology



Model Selection :

- Model Testing : Evaluated LDA, Logistic Regression, Decision Trees, Random Trees, Catboost, XG Boost.





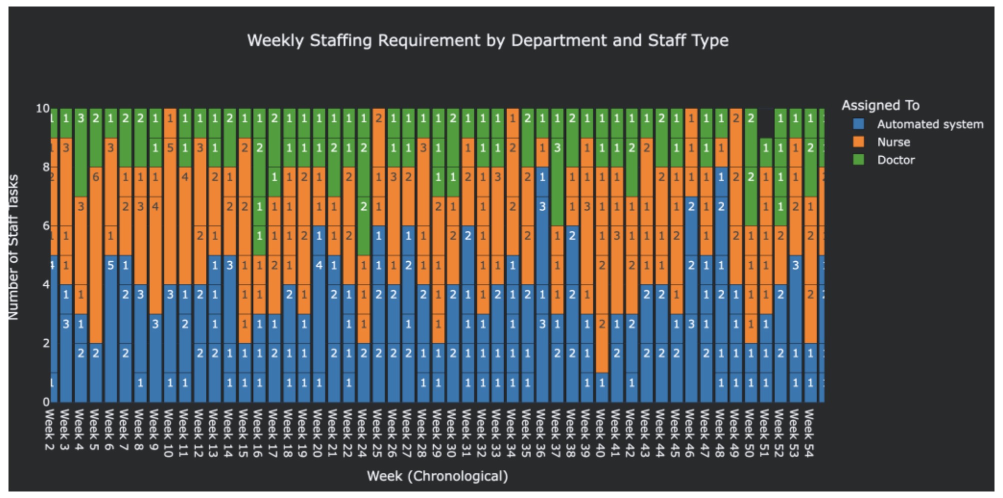
- The Logistic Regression model balanced precision and recall, meaning it not only predicted readmissions accurately but also minimized false positives.

Risk Scoring and Follow-up Communication :

- After Logistic Regression model predicted weather the patient gets **readmitted or not**, with **contextual data** such as weather, air quality, and holidays.
- Based on these predictions the patients are classified into actionable tiers such as High-risk(p >=0.6) → Doctor, Moderate(p >= 0.3) → Nurse call, Low(p<0.3) → Automated SMS.

encounter_id	medical_specialty	Probability	Risk Score	week_num	follow_up_days	follow_up_method	assigned_to
12522	Unknown	0.222415	Low Risk	0	14–30 days	Automated SMS/Email	Automated system
15738	InternalMedicine	0.380105	Medium Risk	0	7–14 days	Nurse call / Teleconsult	Nurse
16680	Unknown	0.003149	Low Risk	0	14–30 days	Automated SMS/Email	Automated system
28236	Unknown	0.479199	Medium Risk	0	7–14 days	Nurse call / Teleconsult	Nurse
35754	Unknown	0.411391	Medium Risk	0	7–14 days	Nurse call / Teleconsult	Nurse

Methodology



RAG (Retrieval Augmented Generation) :

- To interpret the results, our system integrates **RAG** with the Logistic Regression model.
- It retrieves context from a curated **knowledge base** (clinical rules, environmental factors, etc) using **SentenceTransformer + FAISS**, then passes it to an **LLM (Qwen-32B)** for reasoning, producing a short output which is a human-readable explanation of *why* a patient is at risk.

✅ Prediction: Not Readmitted (Low Risk)

Confidence: 0.13

Follow-up Plan: Low Risk → Automated SMS/Email (14–30 days) by Automated system

External Context: { "tavg": -5.8, "pm25": 25.372559214988254, "holiday_flag": 1, "prcp": 0.0 }

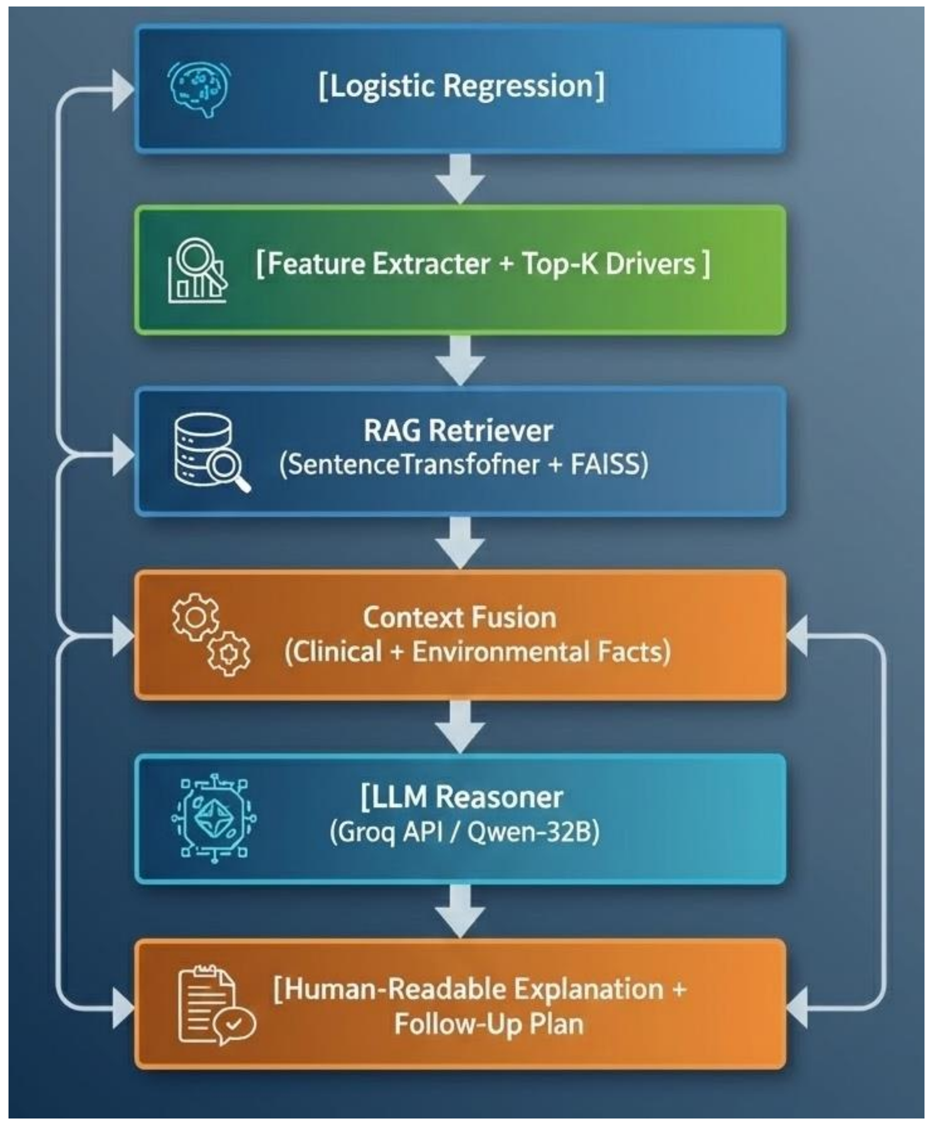
AI Clinical Reasoning

Okay, let's tackle this. The user wants a 3-sentence reasoning combining patient features and environmental effects, plus a follow-up suggestion. First, looking at the patient features: insulin is 1.0, which might indicate they're on insulin therapy, possibly for diabetes. Medical specialty is Internal Medicine, so maybe they have chronic conditions. The other meds like metformin are 0, so not taking that. Change is 1.0, maybe indicating a recent change in treatment or condition. The rest of the specialties are false, so no Psychiatry, Oncology, etc. Now, the environmental factors: temperature is -5.8, which is really cold. High PM25 (25.37) which is moderate but could affect someone with respiratory issues. Public holiday flag is 1, so maybe less access to follow-up due to holidays. No precipitation, so maybe no rain to hinder travel, but cold could still be an issue. The model predicts not readmitted with low confidence (0.1285). That's a

Conclusion

- Integrating clinical and contextual intelligence, our Logistic Regression + RAG system transforms predictions into clear, actionable insights.
- It not only identifies high-risk patients but also explains *why*, guiding timely interventions and personalized follow-ups.
- By merging data accuracy with interpretability, it makes healthcare more proactive, transparent, and human-centered.

System Architecture: RAG-Driven Explainability Pipeline



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