

## MAIS 202 – Project Proposal

**Title:** Early Sepsis Risk Prediction

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### 1) Choice of dataset

We will use [**Dataset: PhysioNet 2019 Sepsis Challenge**], which provides **hourly time-series** of vitals and labs (e.g., heart rate, mean arterial pressure, respiratory rate, temperature, WBC, lactate, creatinine) and a timestamp for **sepsis onset**. These research-grade datasets are large, standardized, and curated for early-warning tasks, enabling reproducible training/evaluation without clinical access. **Educational demo only; not a medical device.**

### 2) Methodology (high-level plan)

**(a) Data preprocessing.** Resample to **hourly**; apply physiologic caps; forward-fill with carry limits; add **missingness indicators**. Engineer features over **1/6/12h** windows (deltas, means, mins/maxes, slopes), time-since-admission, and simple treatment flags if present. Split **by patient** into train/val/test (no leakage).

**(b) Models. Baseline:** LightGBM with class weighting + early stopping. **Stretch:** GRU or Temporal Fusion Transformer with masking; focal loss for rare positives. **Calibration:** temperature scaling so  $0.18 \approx 18\%$  risk. **Explainability:** SHAP (global + per-patient) and partial-dependence for key vitals.

**(c) Evaluation & feasibility. Primary:** AUROC, **AUPRC** (imbalance), Expected Calibration Error (ECE), reliability plots. **Operational: Sensitivity at fixed FPR** (e.g., 20–30%) and **Lead Time** (avg hours before recorded onset when an alert would fire). **Baselines:** majority class, SOFA-like rule, and “last-value only” logistic regression. **Error analysis:** subgroup slices (age/sex/ICU type) where available.

### 3) Application (webapp)

An **educational demo** that visualizes risk over time with transparent reasons.

- **Input:** choose example patient or upload CSV of hourly vitals/labs.
- **Output:** (1) 6-hour risk timeline, (2) adjustable alert threshold with **alerts/day** estimate (alert burden), (3) top contributing features per timestamp (SHAP), (4) simple “what-if” sliders (e.g., **+5 MAP  $\rightarrow$  risk  $\downarrow$ x%**).
- **Tech:** Streamlit or React+FastAPI; saved model (pickle/onnx); small sample cohorts bundled.

### 4) Baselines, metrics, targets

**Baselines:** majority class; SOFA-like heuristic; last-value logistic regression.

**Targets (dataset-dependent):** **AUPRC  $\geq 0.30$ – $0.35$ , AUROC  $\geq 0.80$ , mean Lead Time  $\geq 4$ h** at  $\sim 25\%$  FPR, **ECE  $\leq 0.05$** . Include a **threshold trade-off table**: Sensitivity / PPV / FPR and **alerts per 24h**.

### 5) Risks & mitigations

Label variability  $\rightarrow$  follow dataset’s definition; document limits.

Alert fatigue  $\rightarrow$  calibrated probabilities; evaluate at fixed FPR + show alerts/day.

Overfitting  $\rightarrow$  strict patient-level split; (stretch) external validation on a second cohort.

Missing/noisy data  $\rightarrow$  missingness flags; robust windowed trends.

### 6) Timeline & repo

**Week 1:** EDA, preprocessing, LightGBM baseline, initial metrics.

**Week 2:** Calibration + SHAP; lead-time & alert-burden analysis; Streamlit demo.

**Week 3 (stretch):** GRU/TFT; external validation; counterfactual UI.